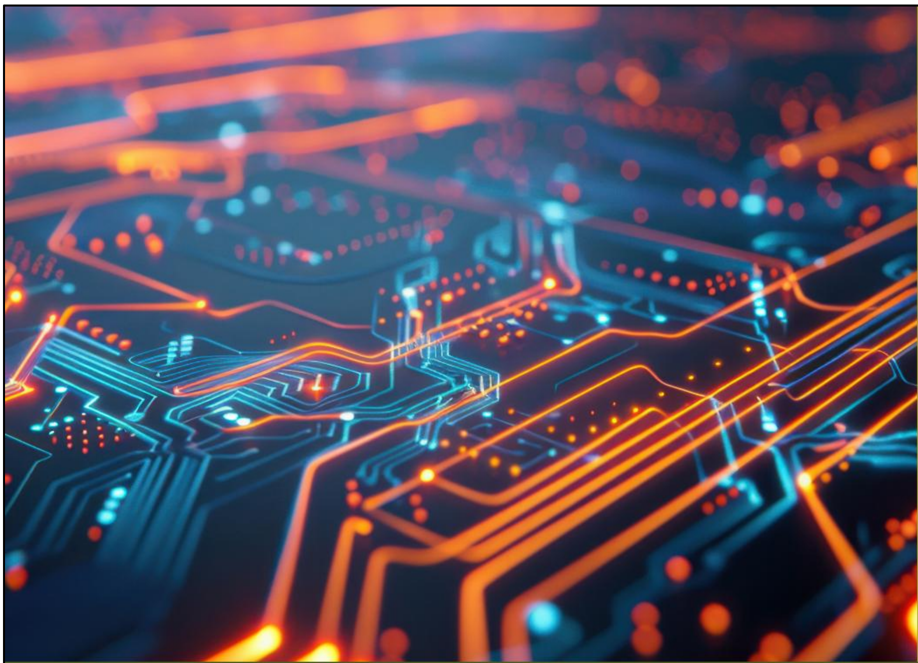

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INNOVATIONS AND RESEARCH IN SCIENCE AND TECHNOLOGY VOLUME III

Editors:
Dr. Tejaswini V. Nandi
Dr. Suhas G. Patil
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Dr. Samir M. Bagade

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PREFACE

Science and technology have always been the driving forces behind human progress, shaping societies, economies, and the quality of life across the globe. In the contemporary era, rapid advancements in scientific knowledge, digital transformation, and interdisciplinary research are redefining how challenges are understood and addressed. The book *Innovations and Research in Science and Technology* is conceived as a scholarly platform to capture these dynamic developments and to present cutting-edge research, critical reviews, and innovative perspectives from diverse fields of science and technology.

This volume brings together contributions from academicians, researchers, scientists, and industry professionals who are actively engaged in expanding the frontiers of knowledge. The chapters encompass a broad spectrum of themes, including fundamental sciences, applied research, emerging technologies, computational tools, artificial intelligence, biotechnology, nanotechnology, environmental science, materials science, and engineering innovations. By integrating theoretical foundations with practical applications, the book highlights how scientific discoveries translate into technological solutions that address real-world problems.

A key objective of this book is to promote interdisciplinary thinking and collaboration. Many of today's complex challenges—such as climate change, sustainable development, health care innovation, energy security, and digitalization—cannot be solved within the boundaries of a single discipline. This volume encourages readers to appreciate the interconnected nature of scientific and technological research and to explore synergies across domains. Each chapter has been carefully selected and peer-reviewed to ensure originality, scientific rigor, and relevance to current and future research directions.

The book is intended to serve as a valuable reference for undergraduate and postgraduate students, researchers, educators, policymakers, and industry stakeholders. We express our sincere gratitude to all contributing authors for their dedication and scholarly contributions, and to the reviewers for their insightful evaluations. It is our hope that this book will inspire innovation, stimulate further research, and contribute meaningfully to the advancement of science and technology in the years to come.

- Editors

TABLE OF CONTENT

IMPLEMENTING ARTIFICIAL INTELLIGENCE TOWARDS ENERGY EFFICIENCY FOR RESIDENTIAL BUILDINGS IN MALAYSIA

Nor Erniamalina Jamaluddin, Nik Norazreen Mohammad Alfaisal, Natalie Ho, Fatin Ain Shafidah Bachik, Ahmad Sulfie Abu Hassan, Klinsmann Anak Robin and Mohd Haris Abdul Rani*

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Abstract:

The problems of high consumption of energy had led to many countries adopting Artificial Intelligence (AI) in spearheading energy efficiency in their buildings. Energy consumption may be decreased by employing AI technology in smart buildings through enhanced control, dependability, and automation. This paper provides a brief overview of recent research on the use of AI technology in smart buildings via the notion of a building management system. In addition to elaborating on the policies and applications of the AI-based energy management approaches used in residential buildings, this paper includes the reality of the wasted energy resources due to the lack of policy to govern AI in Malaysia. Hence, this paper reviews how the implementation of AI in residential buildings in Malaysia will help increase energy efficiency by providing a background of AI in the energy sector, examining the AI policy in Malaysia and learning the experience from other developing countries implementing AI.

Keywords: Artificial Intelligence, Energy Efficiency, Residential Buildings, Policy, Energy Consumption.

Introduction:

According to the Energy and Natural Resources Minister, electricity usage by residential users in Peninsular Malaysia soared 23% during the movement control order (MCO) period (Malays Mail, 2021). The lockdown has caused the citizens to stay at home to be quarantined, thus restricting social activities. Therefore, there is a significant increase in energy consumption at home. Given the fact that the TNB had introduced flexi payment to decrease the burden for residents from unreasonable charges, this had caused residents to take advantage of consuming high amounts of energy (IEPRE, 2021). Consequently, the consumption had caused waste in energy usage which resulted in energy inefficiency. Hence, a new alternative, that is Artificial Technology (AI) is introduced to curb this energy inefficiency. AI technology has the ability to perform cognitive functions in order to solve problems in a way that humans are incapable of. This is because AI is able to solve problems without depending on any teaching algorithm (Abdul Manap & Abdullah, 2020). The introduction of smart buildings is the most promising application of AI in residential energy systems (Farzaneh *et al.,* 2021). Smart buildings are outfitted with a variety of sensors, subsystems, and actuators, and their advanced and smart automation monitoring and control tools can be used to save energy (Raza, 2015). These decreases in energy consumption will help decrease greenhouse gas emissions (Ullah, 2020). It was demonstrated that smart buildings have the potential to protect the environment, reduce building operating costs, and conserve energy in urban areas (Yang, 2019).

Methodology

We conducted our study using library-based research, informed by doctrinal insight, as it is ideal for in-depth research particularly on a new development area on AI, given the extensive research by professionals on the intersection of humanities and law. This method would bring about the needed discussion in exploring the topic in depth. However, due to the rapid development of AI, there is still limited knowledge and articles about it.

Conceptual Framework

According to Russel and Norwig, although there is no exact definition for AI, it can be accepted that AI are machines that are capable of performing tasks to achieve goals and this is due to its machine-learning capabilities (Russel, 20029). There are various applications of AI in our lifestyle which includes Smart home technology whereby AI is integrated into household appliances that assists in minimising electricity usage (FutureBridge, 2021).

As for energy efficiency, its concept has become an importance to the emergence of energy law. It is identified when the maximum benefit of the energy resources is gained while maintaining minimal environmental damage. That being said, energy efficiency is extremely essential especially to consumers in order to sustain the resources and avoid scarcity in the future (Türkoğlu, 2018).

The theory behind energy efficiency is related to philosophers Plato and Aristotle in which both discussed virtue. Though their means to achieve virtue is different, it can still be instilled that an act must be done to achieve an outcome that benefits the self and others. In relation to energy efficiency, it conceptually aims to achieve a maximum benefit of energy, which is considered the 'virtue' by Aristotle and Plato, but at the same time the means must balance with the damage to the environment that must be kept at the utmost minimal.

In this article, it is our hope that energy efficiency in residential buildings can be achieved, especially during the COVID-19 pandemic and this may be done through the usage of AI as the relationship between AI and energy efficiency is crucial in realising this goal while minimising environmental waste. The presence of AI technologies in smart buildings is becoming increasingly evident as technology develops. The development of more energy-efficient sensors and control protocols, in tandem with improvements in hardware and software technologies, enables easier methods of assessing, monitoring, and engaging with the environment. With reduced operational rates and reduced energy consumption, as well as simultaneous improvements in the comfort level and safety conditions for building occupants, efficiency is continually being increased together with the application of AI.

Policy

AI Policies in Malaysia

Currently, there is still no comprehensive policy governing AI in energy efficiency or AI in general by Malaysian policy makers. However, in 2019, former Communications and Multimedia Minister, Gobind Singh Deo had proposed to the Cabinet to implement a National Data and AI policy by mid- 2020 in complementing the upcoming National Artificial Intelligence Framework (Nair, 2019). Since the application of AI in Malaysia is still new, the policy makers should start regulating AI for it to be legally accepted in Malaysian industries.

The guidelines suggested by Abdul Manap and Abdullah (2020) in regulating AI in Malaysia includes the two-tier approach where the first-tier refers to a specific Act of Parliament on AI that should include elements like definitions of AI, certification requirements, specific area for AI and digital peculium while the two-tier refers to the policy and directives given by the government.

As AI possesses excellent benefits, it also causes harm to humans. Recent events have shown AI to be imperfect (Sipper & Moore, 2017). The absence of an AI regulatory framework would bring infringement of fundamental rights. For example, data collected by AI may cause undesirable effects on human rights due to the bias feature of AI. Other than that, AI may cause privacy and cyber security issues, despite having implemented the Personal Data Protection Act and Computer Crimes Act 1997 to combat such threats (Abdul Manap & Abdullah, 2020). Therefore, due to the rapid growth of AI, comprehensive regulations are needed to address the legal issues in AI particularly in the energy sector.

Energy Efficiency Policies in Malaysia & Other Countries

The Ministry of Energy, Green Technology, and Water developed the National Energy Efficiency Action Plan (NEEAP) in 2015, which is a comprehensive policy for application of energy efficiency measures in the industrial, commercial, and residential sectors, resulting in lower energy consumption and cost benefits for end users and the nation (Ministry of Energy, Green Technology and Water [KeTTHA], 2015). However, the NEEAP only focuses on electricity usage and does not cover the other aspects of the energy sector. Specifically for buildings, the NEEAP had been proposed under Key Initiatives 5 for the energy efficient building design. Surveys by the Ministry of Energy, Green Technology and Water found that the commercial sector utilises around one-third of all power consumed in the country, with a major portion of this consumed in buildings for cooling, ventilation, lighting, appliances, and so on. As a result, a programme to guarantee that these new buildings are designed and built with energy efficiency in mind is critical. For example, in NEEAP, we could already see in 2012, the promotion of energy efficiency in new commercial buildings was made mandatory by the amendment of the Uniform Building By-Laws (UBBL). In the UBBL, the section also requires those buildings to be provided with an Energy Management System (EMS), which is a computer- aided tool in managing energy for commercial buildings.

In addition, under the Ministry of Housing and Local Government, the Malaysia Smart City Framework (MSCF) was developed considering the importance of smart cities development when implemented in Malaysia (Ministry of Housing and Local Government [KPKT], 2018).

The Government of Malaysia believes that Smart City can improve the management and development of urban planning including to give solutions in combating urban issues such as environmental pollution and traffic congestion. The MSCF is also established to meet national and global agendas, especially towards achieving the objectives of the Sustainable Development Goals, keeping Malaysia at the same pace as the global urban development trends.

Meanwhile in the USA, the policies of AI in the US do not cover the energy sector, thus resulting in no comprehensive AI policies in energy efficiency. The existing AI policies only cover the development of emerging technology, AI education plan and AI R&D (OECD, 2021). However, in 2018, IBM's DeepMind applied AI to 700 MW of Google's wind power capacity in the central USA in order to power a medium-sized city (DeepMind, 2019).

On the other hand, there is a company in Norway which uses AI in electric consumption known as Elvia. It focuses on efficiency in operating the electricity grid by gathering data through machine-learning, which produces nearly 5 billion KWh renewable energy. The company also attempts to reinvent energy systems through their predictive maintenance and Connected Drone through deep learning. Not only that, the company also aims to ease consumers in realising energy consumption through Connected Prosumer which provides visualization of energy consumption detailed to the preferences of the consumer (Moltzau & Bouwer, 2020).

As for International Energy Agency (IEA) countries, there exist comprehensive energy policies to promote energy security among its member countries (International Energy Agency, 2017). For instance, the Research Council of Norway invested in a programme called ENERGIX which is a competence building project. Not only that, EarlyWarn actively uses AI and machine learning in their systems to consistently keep track on sensor data automatically to warn operators of any unnoticed inconveniences (Andresen, 2017).

Suggestions for Implementation of AI and Energy Efficiency Policy

Based on the research, we propose for the NEEAP policy to be broader and cover the implementation of AI by considering the guidelines on regulating AI in terms of security and privacy and also in accordance with the NEEAP itself. As for the AI regulations, the Ministry of Communications and Multimedia should start regulating comprehensive policy to control the conduct and ethics of AI. Moving on to implementing AI in energy efficiency, the insertion of AI in the NEEAP is a good start to align with the objective to achieve energy efficiency as currently there is no comprehensive policy focusing on energy efficiency of residential buildings. As provided in the NEEAP, where the UBBL mandated the commercial buildings to comply with the Energy Management System (EMS). Hence, this part should be widened not only to commercial, but to also include the residential buildings.

A suggestion that can be introduced is by including AI in the cooling and ventilation system in residential areas as an AI-based AC can promote energy while reducing costs (Kannan, 2020). This suggestion is aligned with Key Initiative 5 of the NEAAP since it covers energy consumption for cooling and ventilation. Other than that, the idea of thermostats that readjust temperatures according to humidity sensors and exterior temperature readings through AI from Toronto- based Ecobee can be taken (Ekanayaka Gunasinghalge *et al.,* 2025).

According to MSCF, implementation of AI in the government's policy can create a more developed nation which has a huge impact on the global economy. This can be seen in the smart city trend which is supported by technological advances such as the Internet of things, Cloud Computing and Big Data Analytics. Thus, it is suggested that Malaysia should welcome this wave of digitalisation and utilise it to improve the quality of life and develop a sustainable nation and this can be done through implementing AI, especially in the energy sector.

In conclusion, AI development has been expeditious which gave impact on the law that had failed to keep pace, and this applies not only in Malaysia but across the world. Today, the law involving AI only covers product safety and consumer protection. Thus, schemes that could speed up the adoption of digital technology such as the National Artificial Intelligence (AI) Framework needs to be implemented as the current legislation in Malaysia are inadequate to tackle complex, ethical and liability issues involving AI. We also believe that the policy makers should start working together to resolve energy inefficiency by adopting new technologies, such as AI, to achieve the goals.

Not only that, but regulations of AI should also involve various ministries in order to establish successful and effective policies. For example, the Ministry of Education may formulate policies on AI Education Plan to increase diligent students in expanding their AI knowledge or to increase R&D. Similarly in the USA, where the NSF AI Research Institutes had established a National AI Research Institute that promotes long-term research on AI and encourages more AI learning with AI based education (OECD AI Policy Observatory, 2021).

Findings

According to Farzaneh *et al.* (2021), smart building is a promising application in promoting energy efficiency in urban areas as it incorporates big data (BD) and sensors as well as utilizing AI (Farzaneh *et al.,* 2021). Vivek Kumar (2018) mentions that using Athena programs in energy storage can promote energy efficiency as it allows the users to track fluctuations in energy rates. This can be seen In Ontario where the timing of peak times is accurately predicted which leads the organizations to decrease their energy usage during this time (Kumar, 2018).

Kane and Ault (2013) disclose that an AI-based software known as Active Network Management (ANM) can be used to handle manifold energy sources simultaneously by tracking the interaction of the grid with various energy loads then changing the grid to enhance energy efficiency (Kane &Ault, 2013). Vivek Kumar (2018) points out that Alphabet's Nest is a smart thermostat for homes which can decrease energy consumption by adapting the behaviour of the users which has been proven to save 10% to 12% monthly energy in the US (Kumar, 2018).

Not only that, Machine Learning as explained by Farzaneh *et al.* (2021) can make accurate predictions of consumer energy use (Farzaneh *et al.,* 2021). Decision Trees can be used to improve energy efficiency by predicting breakout risk, storing energy and managing energy in buildings. For instance, the New England 39-bus test system is utilized in showing the benefits of the proposed algorithm. Next, Naïve Bayes is used in the UK to solve energy problems in building by calculating the probability of a prediction beforehand. For instance, building energy efficiency datasets and prediction of photovoltaic energy (Ahmad *et al.,* 2017).

In a nutshell, even though AI is widely used to enhance energy efficiency in most countries, the main challenge regarding the deployment of AI policies in energy efficiency concerns the accountability, accuracy, explainability, transparency, reliability and resilience of the AI system (Future of Life Institute, 2020). This situation requires the development of policies governing human-AI issues whereby the future developments of AI policies must be trustworthy human-centered systems. The policy-maker must recognize that AI is to be implemented together with continuous development of AI policy. In Malaysia, Teoh *et al.* (2020) points out that Malaysians' attitude towards energy-conserving behavior is disappointing. Even though they are aware of solar energy as an alternative for energy conservation, they are not willing to install solar photovoltaic due to the high cost (Teoh *et al.,* 2020). Thus, if the deployment of AI policies in energy efficiency is to be implemented in Malaysia, we need to first consider the installation cost as not many people are able to afford it, especially considering the Covid-19 pandemic which has affected many people in terms of their financial ability. As for Malaysian's energy-conserving behavior, setting policies and strategies to reduce the installation cost is an important step to be considered.

Recommendations

Based on the challenges presented there is a need for ethical, technical and legal integration to further enhance the AI in residential energy efficiency which cannot rely only on technical solutions or even market incentives. A multi-pronged approach which involves legal foresight, cultural sensitivity and ethical accountability being synthesized into proposed policy pathways and added governance strategies for improving the gaps, thus ensuring a just, inclusive and sustainable AI powered energy future for Malaysia. Perhaps this would also be a lesson to be learned by other nations in the same dilemma.

It is imperative that Malaysia to adopt a coherent, forward-looking strategy for the integration of AI into residential energy system. This must be balanced with dual imperatives of technological innovation and ethical governance. This is to ensure the deployment of AI tools efficiently and help ensure such deployment will contribute meaningfully towards sustainability goals, energy justice and public interest.

A phased strategy should ensure a controlled introduction and a gradual AI-based energy system, reduce risks and build institutional learning over time. The roadmaps are as follows:

- Phase 1: Awareness and Capacity Building (Year 1-2). This phase mainly focuses on public education, pilot programme and also various technical training. Targeted awareness campaigns would enlighten AI benefits for homeowners and address common fears. Concurrently training initiatives created for policymakers, legal professionals and energy editors to make them familiarize with AI technologies and the governance needed.
- Phase 2: Pilot Regulation and Regulatory Sandbox (Year 2-4). An introduction of a regulatory sandbox framework mainly for AI in the energy sector would enable developers to implement safely new technologies withing the regulated boundaries. This could be done through oversight and evaluation by empower bodies identified to conduct supervisory monitoring and evaluation. Gathering lessons from these projects can be valuable information to national regulatory bodies and identify risks before a full-scale deployment.
- Phae 3: National Integration and Standards (Year 5 onwards). Based on the pilot project's outcome, the central government should be able to roll out AI standards for residential energy systems. They include interoperability protocols, data privacy and ethical benchmarks. Then these standards can be regulated into law and enforced by relevant agencies.

In order to support this avenue, Malaysia should re-evaluate existing laws and policies, as well as develop new ones that suit the demands of AI. Amend the Personal Data Protection Act (PDPA). The PDPA needs to be revised with sections on algorithmic transparency, automated decision-making and user redress mechanisms. Consent should be granular and informed, particularly for passive collection of data in homes. Inspiration can be had from the EU-GDPR, which explicitly refers to AI and profiling risks.

Clarify Liability and Accountability Structures. Every legal instrument must be able to be audited and specify legal liabilities of those responsible if AI systems don't work properly or cause injury, this involves the device maker and software provider, the energy supplier, or even users at their point of operation. This is to warrant that any normalisation of the consideration of AI risks in all contractual relations where they are incorporate AI risk clauses and identify the regulatory bodies which will develop sector-specific liability guidance.

The Establish an AI-Energy Governance Commission. A multi-sector regulator, exclusively for the energy sector, should be established to control AI governance. This commission would oversee ethical adherence, examine algorithms models for bias and periodical consultation with the public. This is seen development with the Malaysia's National AI Framework (NAIF) (2023) that intended to formulate a comprehensive and strategic governance principles for AI, including ethics, accountability, and public consultation and also the Malaysia Digital Economy Blueprint (MyDIGITAL) (2021)

Integration of ethical codes in to Public Procurement. New government housing which incorporates AI energy systems need to meet ethical procurement standards. These might be sustainability standards, transparency requirements and obligations to consult with stakeholders.

Conclusion:

AI is indeed a successful alternative in increasing energy efficiency by looking at other developing countries in implementing AI in the energy sector. However, in accordance with the continuous growth of AI technology, comprehensive and pragmatic changes in the law and policies are needed as mentioned earlier in this paper. Laws concerning the consumption of energy are very much needed in Malaysia, to increase energy efficiency in the buildings. Therefore, enhancement to the current existing policy, NEEAP, had to be done by the government immediately.

In regulating the new law, a reference to Norway and USA can be conducted to adopt useful law and regulations whichever suits Malaysia's circumstances. In the effort in implementing the new law, the parliament also has to allocate certain revenue for the deployment of AI systems into Malaysia as it can be costly for the citizens especially for the installation.

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AI IN CYBERSECURITY: A SYSTEMATIC ANALYSIS OF THREAT DETECTION AND DEFENCE MECHANISMS

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Abstract:
The overdevelopment of the digital technologies, both cloud systems, and mobile devices, and mass IoT systems made the environments very connected and more susceptible to the cyberattacks. The outdated rule-based security systems, because of the clever and computerized methods which perpetrators are using to infiltrate systems, seldom contain discourse of the more advanced and occasionally unfamiliar or fast-evolving attacks. Artificial Intelligence (AI) has proved to be a necessary component of the enhancement of cybersecurity in this dynamic environment as it can learn and make decisions based on the data and discover the hidden features as well as make real-time decisions. The paper examines the methods of improving threat detection, accuracy of detection, and eliminating false alarms that are all imposed by the AI-driven models in contemporary cybersecurity. Machine learning, deep learning, natural language processing, and behavioral analytics allow AI systems to process large amounts of network traffic, user behavior logs, and system events and detect trends, which could be led by malware, phishing, intrusions, or insider abuse. The further contribution by reinforcement learning is that it provides adaptive defensive mechanisms that evolve with the evolving techniques of attack. In the paper, it is also discussed that the main barriers to the AI implementation in cybersecurity are threat of malicious attacks of AI models, complexity of acquiring high-quality data, the issue of the explainability and transparency of AI-based decisions, and the ethical issue of extensive surveillance. Regardless of all these considerations, this research paper shows that AI is becoming the key to the development of proactive, smart, and robust defensive solutions. The future of cybersecurity solutions is also on the territory of the AI that will allow analyzing the future and using automatic response, which will, in its turn, enhance the security posture of digital ecosystems in general.

Keywords: Artificial Intelligence (AI); Cybersecurity; Machine Learning; Threat Detection; Intrusion Detection System (IDS); Adversarial Attacks.

1. Introduction:

High-speed digitalization of finance, healthcare, governance, education, and vital infrastructure has raised the radical use of interdependence and real-time sharing of data. Although this change has resulted in increased speed in innovation and efficiency, it has resulted in an enormous and vast attack space that is in the possession of cybercriminals. The previous methods of cybersecurity which are mostly signature detection, pre-programmed rules and human observations are no longer able to deal with the technicalities, speed, and volumes of the contemporary cyber threat. Attackers have become very dynamic such as polymorphic malware, ransomware-as-a -service, automated exploitation tools and advanced persistent threats which are also evolving at a rapid pace compared to human operated defense systems that are unable to counter the attackers [1]. This further drives the cybersecurity landscape in the world towards the requirements of smarter, more proactive, self-initiatives of protection.

The use of Artificial Intelligence (AI) is currently among the most groundbreaking technologies regarding the solution to these problems. With the help of machine learning, deep learning, natural language processing, and reinforcement learning, AI-enabled cybersecurity systems can be constantly trained based on the information, identify the distinctive changes in behavior, and react to the threats that have not been previously known. Contrary to conventional tools that may not be ready to process huge amount of network logs, system event logs, and user activity patterns, AI models can process them on machine speed hence provide organisations with a more insightful view and predict threats before they happen. It is simple to implement automated incident response by utilizing AI thereby minimizing the human error and enhancing security operations center (SOCs) efficiency. Also, AI is being used in the classification of malwares, detection of phishing, vulnerability examination, fraud detection, and cloud security, which implies that AI could transform the current cybersecurity paradigm. Nonetheless, AI implementation in the realm of cybersecurity also has its issues. Adversarial machine learning, data poisoning, algorithmic bias, model explainability, and real-time decision accountability are also issues that add extra risks that require careful management [2]. More attackers are also targeting AI systems directly, by being able to manipulate them in order to evade detection or arrive at false results. Hence, the security, transparency, and resilience of AI-based defenses have become a research field of great importance.

Considering the increasing importance of AI-based security solutions, the current research paper will offer an overview of the role AI methods play towards the improvement of threat detection, analysis, and response. The paper also brings out the new trends, constraints and future opportunities in this fast-changing area.

To provide a structured understanding of these issues, the remaining sections of this paper are organized as follows:

- **Section 2** discusses the role of AI in modern cybersecurity and how it shifts security from reactive to proactive models.
- **Section 3** presents key applications of AI in cybersecurity, including intrusion detection, malware analysis, phishing detection, and behavior analytics.
- **Section 4** explains major AI and machine learning techniques used in cyber defense.

- **Section 5** highlights the challenges, limitations, and risks associated with AI-powered security systems.
- **Section 6** concludes the paper, summarizing key insights and emphasizing the importance of AI-enabled defense mechanisms.

2. The Role of AI in Modern Cybersecurity

Artificial Intelligence (AI) has radically transformed the cybersecurity arena by transforming the conventional defense tactics based on reactive to superior and proactive techniques. The use of more sophisticated cyberattacks, which may be fileless malware or Multi-stage APT, requires the use of more traditional approaches to intrusion detection, antivirus systems, and single firewalls [3]. In a way, AI supports the concept of cybersecurity and helps organizations notice, analyze, and react to attacks at a scale that has never been seen before due to the incorporation of autonomous learning, adaptive behavior modeling, and predictive analytics. AI transforms cybersecurity from reactive to proactive defense through:

2.1 Real-Time Threat Detection

The detection mechanisms of AI are based on machine learning, deep learning, and behavioral analytics to analyze network traffic, system logs, user sessions, API calls, and endpoint activities in real-time. These models can distinguish between normal and abnormal behavior patterns and hence, malware, brute-force, unauthorized access, privilege escalation and insider attacks could be identified instantly. Unlike signature-based tools, AI systems use behavior analysis rather than pre-defined behaviors to detect polymorphic malware and zero-day exploits. In addition to saving a great deal of time in response, this real-time detection feature makes security infrastructures more resilient.

2.2 Predictive Threat Intelligence

One of AI's most potent contributions to cybersecurity is predictive analytics. In order to identify patterns that may indicate future threats, machine learning algorithms analyze historical attack data, threat intelligence feeds, vulnerability reports, social engineering trends, and open-source intelligence (OSINT) data. These systems can anticipate potential attack vectors, target exploit or novel malware family and these organizations can raise defenses before an actual attack occurrence has transpired [4]. AI predictive threat intelligence will help to actively minimize a risk, fix vulnerabilities early and more thoroughly examine high-risk assets.

2.3 Automated Defense and Incident Response

A variety of degrees of cybersecurity activity can be automated with the help of AI, in particular, SOAR (Security Orchestration, Automation, and Response) platforms. These systems have automatic searching of alerts, cross-source event correlation, incident classification, and the triggering of corresponding containment actions. Tasks such as isolating hacked hosts, filtering rogue IPs, user account restarting, generation of forensic records and activation of backup tools can be automatically undertaken with very minimum human intervention. Automation is faster in establishment of response cycle; it minimizes the workload of the analysts and it provides uniformity in applying security policies to the organization [5].

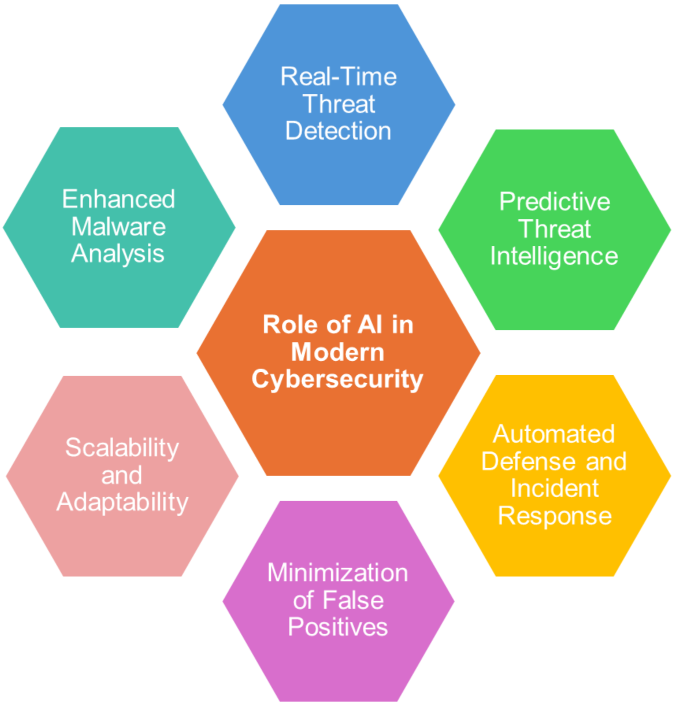

Figure 1: Role of AI in Modern Cybersecurity

2.4 Minimization of False Positives

Conventional intrusion detection systems (IDS) can tend to produce high amounts of false positive alerts which can overwhelm security teams and make them risky in regards to missing out on real threats. The AI improves accuracy in alerts achieved by intelligent filtering, contextual awareness and learning. Models adjust themselves with time depending on the feedback of analysts and network environment. This minimizes alert fatigue and boosts the effectiveness of SOC, allowing the specialists to concentrate on validated and high-priority security incidents.

2.5 Scalability and Adaptability

AI-powered security systems are highly scalable, and this allows them to be used in cloud environments, hybrid-systems, distributed systems, and enterprises with billions of log events per day. With the growth of networks and the number of connected devices, AI models can be scaled horizontally without compromising the quality of detection [6]. Their adaptive learning ability allows them to keep improving and as a result, they evolve due to new attack schemes, altered network behavior, and active threat surfaces.

2.6 Enhanced Malware Analysis

AI assists with dynamic and static malware Analysis by categorizing malicious files, identifying code obfuscation, detecting atypical execution behavior, and evaluating sandbox behavior [7]. Opcode sequence, API call trace, and binary feature models can identify unknown malware without signature updates due to deep learning training. This enhances threat research laboratories as well as endpoint protection systems.

3. Applications of AI in Cybersecurity

Artificial Intelligence became a part of a contemporary cybersecurity system. Its capability to learn patterns, uncover anomalies, and make decisions automatically allows organizations to react to threats more swiftly, precisely and effectively. The applications of AI include network security, endpoint protection, fraud detection, cloud governance, internet of things protection, and threat intelligence. Table 1 gives the brief explanation of Artificial Intelligence in Cybersecurity.

Table 1: Key Applications of Artificial Intelligence in Cybersecurity

Application Area	Brief Explanation	AI Techniques	Key Benefits
IDPS (Intrusion Detection & Prevention)	Detects abnormal network behavior and blocks attacks.	Supervised/Unsupervised ML, Deep Learning	Detects zero-day attacks, real-time threat alerts
Malware Detection & Analysis	Identifies polymorphic, metamorphic, and fileless malware.	LSTM/RNN, Autoencoders, GNNs	Better accuracy, detects new malware variants
Phishing Detection	Analyzes emails, URLs, and content to detect scams.	NLP models (BERT, Transformers), URL classifiers	Reduces phishing risks, detects fake pages & QR scams
UEBA (User & Entity Behavior Analytics)	Monitors user/device behavior to detect insider threats.	Anomaly detection, Behavioral models	Detects unusual logins, data exfiltration, privilege misuse
Threat Intelligence	Converts large security data into actionable insights.	Clustering, Classification, Predictive Analytics	Detects campaigns, prioritizes vulnerabilities
IoT & Cloud Security	Monitors devices, APIs, and cloud configurations.	Lightweight ML, IAM anomaly detection	Prevents botnets, misconfigurations, and access misuse

4. AI Techniques Used in Cybersecurity

To identify, evaluate, anticipate, and lessen cyberthreats, artificial intelligence makes use of a variety of computational models and learning techniques. Compared to conventional rule-based methods, these techniques greatly enhance defense capabilities by making cybersecurity systems more accurate, autonomous, and adaptive. The main AI techniques used in contemporary cybersecurity settings are expounded upon in the ensuing subsections.

4.1 Machine Learning Algorithms

AI-driven cybersecurity is built on machine learning (ML), which allows systems to learn from past data and instantly recognize new threats. ML algorithms are widely used to identify anomalies, detect intrusions, classify traffic behavior, and forecast the likelihood of attacks based on changing threat patterns [8].

Commonly applied ML techniques include:

- **K-means clustering** – Groups network traffic into clusters, helping identify outliers indicative of unknown attacks.
- **Random Forest** - Ensemble classification that improves prediction accuracy in detecting malware and intrusion attempts.
- **Support Vector Machines (SVM)-** In high-dimensional threat datasets, SVM accurately distinguishes between benign and malicious behaviors.
- **Naive Bayes** - This fast probabilistic classifier is used for fraud detection, phishing detection, and spam filtering.
- **Gradient Boosting (XGBoost, LightGBM)** – This technique works well for prioritizing threat alerts and ranking vulnerabilities.

4.2 Deep Learning Techniques

By identifying intricate, non-linear patterns in massive datasets like packet captures, binary malware samples, and user logs, deep learning (DL) improves cybersecurity [9]. In situations where threats change quickly and disguising techniques are prevalent, DL models perform better than traditional ML.

Key deep learning models used include:

- **Convolutional Neural Networks (CNNs)** – Convert malware binaries into images for classification; used in packet inspection and encrypted traffic analysis.
- **Recurrent Neural Networks (RNNs) and LSTM models** – Analyze time-dependent threat sequences such as brute-force attempts, botnet communications, and log activities.
- **Autoencoders** – Learn baseline system behavior and flag deviations for anomaly detection in IoT and industrial networks.
- **Generative Adversarial Networks (GANs)** – Generate synthetic attack datasets to improve model robustness and detect adversarial manipulation.

4.3 Natural Language Processing (NLP)

NLP makes it possible for cybersecurity systems to examine human-generated content, which is essential because many attacks take advantage of social engineering and written communication.

NLP methods are employed for:

- Semantic and sentiment analysis-based phishing email detection
- Predicting malicious URLs and domains
- Identification of fraudulent messages and spoofed identities

- Detection of obfuscated or embedded malicious scripts
- Analysis of social engineering indicators in chat, SMS, and social platforms

4.4 Reinforcement Learning (RL)

Reinforcement Learning supports autonomous cybersecurity systems capable of learning optimal defense strategies through continuous interaction with network environments [10].

RL is used for:

- Dynamic firewall and access-control rule tuning
- Adaptive intrusion detection that evolves with attacker tactics
- Optimizing routing decisions to mitigate DDoS attacks
- Honeypot behavior adaptation to study adversaries
- Automated response decision-making in SOAR platforms

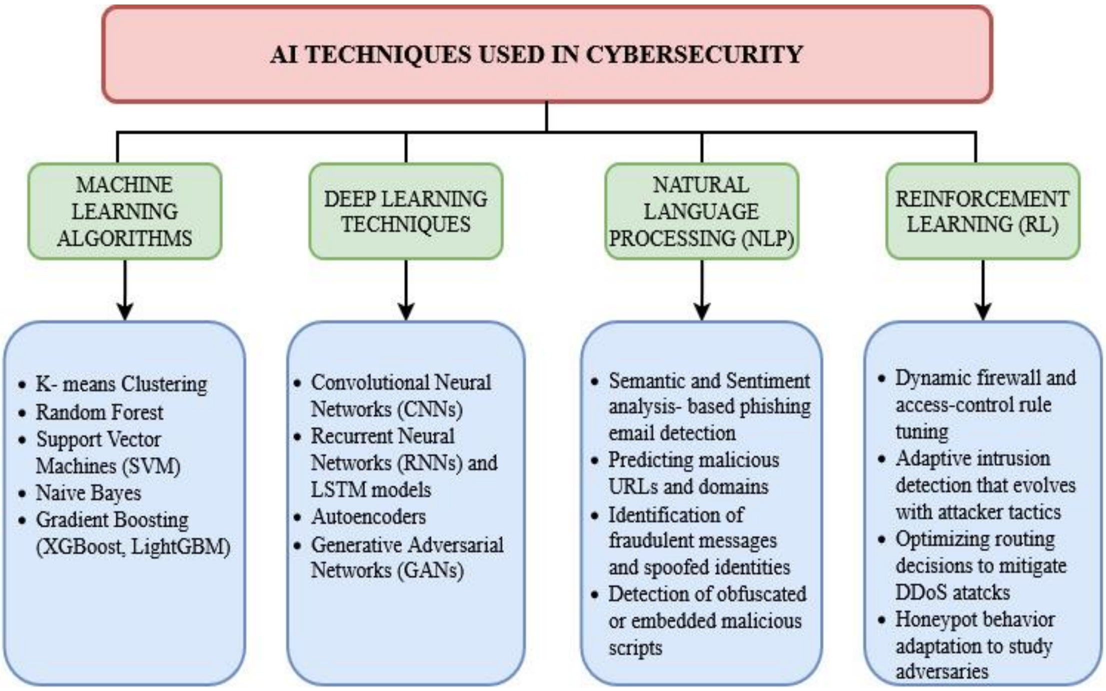

Figure 2: AI Techniques used in Cybersecurity

5. Challenges and Limitations of AI in Cybersecurity

5.1 Adversarial Machine Learning

The threat of adversarial machine learning where attackers strategically alter inputs to mislead AI models is one of the key issues in the implementation of AI to cybersecurity. Cybercriminals can make AI-based detection systems misclassify malicious artifacts as safe by slightly altering malware signatures, altering packet structures, or rewriting phishing messages [11] [12]. This complicates the detection of attacks and allows ill-intended people to evade advanced filters. Consequently, the AI-based defenses need to be continually trained to improve security as a result of adversarial training, robustness testing, and model hardening methods to eliminate the usage of model vulnerabilities.

5.2 Data Scarcity and Quality Issues

AI models need massive amounts of high-quality, varied, and labeled cybersecurity data, and this data is not readily available because of privacy issues, security secrecy, and the paucity of available real-world attack data. There is a reluctance to disseminate breach information in organizations and labeling network logs or malware samples involves experts making it more expensive and complex. Bad or unfinished datasets contribute to biased models that can only work well with threats that have been encountered before, rather than on unknown or uncommon attack patterns. Such a limitation decreases the level of reliability and compromises the capability of AI to detect zero-day threats.

5.3 Computational Overheads

Introducing AI in cybersecurity creates serious computational and infrastructure requirements, particularly when deploying deep learning models which involve strong processing units, vast memory, and fast storage systems. Training and implementation of these models like the real time intrusion detection or large scale log analysis may be expensive and power intensive. The vast majority of small organizations may struggle to operate AI-based security systems effectively and latency may pose an issue in situations that require responses in real-time [13] [14]. This becomes a barrier to adoption and forces security teams to make performance and cost trade-offs along with deployability.

5.4 Overfitting and Model Drift

The other weakness is overfitting and model drift in which AI systems cannot work effectively in changing times in cyber threats. An overfitting model is unable to perform in the real-life case where it cannot predict the situation accurately when it involves real-life attacks, particularly when it is trained on too specific patterns that it can no longer be trained on.Model drift occurs when the behavior of users or the network conditions change or the attacker methodologies, and hence the earlier models that were used to work correctly begin to start performing at a worse level. In order to be effective, AI systems need to be regularly retrained, updated and adapted, which takes time, expertise and constant monitoring [15].

5.5 Ethical and Privacy Concerns

The issue of AI in cybersecurity is also associated with ethical and privacy concerns because most AI-based security systems are based on surveilling users, examining their communication patterns, and gathering behavioral data. Such monitoring without a right regulation and protections may interfere with the personal privacy, breach the compliance policy, and provoke the fear of surveillance and abuse [16][17]. Additionally, AI systems may be biased because of the data they are trained on, which may result in prejudiced or discriminatory security decisions. To ensure trust, transparency, and accountability in AI-driven security activities, it is necessary to ensure that they meet the requirements of privacy laws, including GDPR and domestic privacy regulations.

5.6 False Positives and False Negatives

AI-powered security mechanisms are susceptible to inaccuracy in classification, which will result in false positive and false negative. False positives create too many alerts on innocuous activities that overload the security teams and lead to alert fatigue, which in turn can lead to actual threats. False negatives are more harmful, however, because they cause malicious activity to slip through the system and allow malicious attackers to compromise systems, steal data, or remain in place long-term [18]. The balance between sensitivity and accuracy is a serious problem and only can be achieved through setting a model and several refinements.

5.7 Dependency on Skilled Workforce

Even with the automation, AI-enhanced cybersecurity systems cannot be designed solely by the computer; professionals should still be involved to create models, analyze the output, handle the threat intelligence, and react to the threats identified [19]. The skills gap is increasing as the number of cybersecurity experts who are also skilled in machine learning is declining, slowing down adoption and causing greater operational risk. The workforce needed to implement AI into the current security systems may be unable to identify or develop employees with the ability to incorporate AI into the system since the talent pool is relatively small, thereby making the implementation more complex and costly.

5.8 Risk of Autonomous Malicious AI

With the increased use of AI in cybersecurity protection, attackers are now using AI to build offensive capabilities. Bad AI can be used to automate vulnerabilities, create adaptive malware that develops to circumvent anti-malware, develop highly authentic deep fake-powered social engineering attacks, and increase the speed of password cracking [20][21]. This puts a new battlefield on which AI systems must fight AI-driven threats and improve the sophistication of the attacks, which necessitates defensive models to become smarter and more autonomous. Any chance of self-education about offensive tools poses a high risk in the future and increases the necessity of active research and regulation.

Conclusion:

Artificial Intelligence has become one of the most radical technologies in contemporary cybersecurity, as it helps organizations transition away from the old defensive methods of security to modern proactive methods of security, adaptable, and intelligence-driven security systems. Through this combination of machine learning, deep learning, natural language processing and reinforcement learning, AI has very high chances of improving the detection of advanced cyber threats such as zero-day attacks, polymorphic malware, insider threats, and advanced social engineering campaigns. The fact that it can process large volumes of data, adapt to changing models of attack patterns and act independently gives AI an irreplaceable role in next-generation cybersecurity infrastructures. The research in this paper has identified the various uses of AI in intrusion detection, malware analysis, phishing prevention, user behavior analytics, IoT protection, and massive threat intelligence. The synergies of these technologies are useful in increasing the overall defense mechanisms and reducing the occurrence of false positive as well as reducing the response time of the incidents and offering the scalable security solutions that can be used in the cloud as well as the distributed environment. Despite all the enormous potential of AI, the adversarial attacks, and the challenges related to data sets, model drift, computational requirements, and ethical concerns related to privacy and transparency are also the Achilles tendinous challenges of AI. In order to address these limitations, continuous model training, appropriate maintenance of the dataset, stricter policies and development of explainable and trustful AI systems are needed. Conclusively, AI is no better than the current state of cybersecurity but a foundation upon which the future security architectures will rest. As the number of cyber threats and the complexity of cyber threats grows, human capabilities will be essential in conjunction with the intelligent automated systems to provide resilient digital ecosystems. Additional studies, collaboration, and advancement will ensure that AI will formidably join in securing networks, information, and global online systems.

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STUDIES ON OPTIMAL GROWTH CONDITIONS FOR *AZOLLA PINNATA* CULTIVATION

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Abstract:

Azolla pinnata, a small aquatic fern belonging to the family Salviniaceae, is recognized for its rapid growth and ability to fix atmospheric nitrogen through a symbiotic relationship with the cyanobacterium *Anabaena azollae*. This study investigates the morphological features of *Azolla pinnata* and examines the effect of temperature on its growth and pigmentation. Experimental conditions included temperatures of 10°C, 28°C, and 40°C. The results revealed that *Azolla pinnata* exhibits optimal growth at 10°C and 28°C, while growth declines at 40°C. The study also reviews previous research concerning the plant's biochemical profile, nutrient productivity under various conditions, and applications as a biofertilizer. Findings confirm that *Azolla pinnata* enhances soil fertility, supports sustainable rice cultivation, and can serve as a valuable bioresource for agriculture and environmental management.

Keywords: *Azolla pinnata*, Symbiotic Relationship, Pigmentation, Biofertilizer, Bioresource for Agriculture.

Introduction:

Azolla pinnata, commonly known as the Asian water fern, is a small, free-floating aquatic fern found widely across tropical and subtropical regions of Asia, Africa, and Australia. Belonging to the family Salviniaceae[1], *A. pinnata* is recognized for its rapid vegetative growth, high biomass productivity, and unique symbiotic association with the nitrogen-fixing cyanobacterium *Anabaena azollae*[2]. This partnership enables the fern to fix atmospheric nitrogen efficiently, making it an important biological fertilizer in sustainable agriculture, particularly in rice cultivation systems.

Beyond its role in improving soil fertility, *Azolla pinnata* has gained scientific interest due to its diverse applications. Its ability to absorb heavy metals and excess nutrients positions it as a promising candidate for phytoremediation and wastewater treatment. Additionally, its rich protein content and favorable nutrient profile support its use as a low-cost feed supplement for livestock, poultry, and aquaculture. Emerging research also highlights its potential in biofuel production, carbon sequestration, and climate change mitigation[3].

Given its ecological importance and broad practical applications, *Azolla pinnata* continues to attract attention as a multifunctional species with significant relevance to environmental sustainability, agriculture, and biotechnology[4]. This paper explores its biological characteristics, ecological roles, and potential uses across various scientific and industrial sectors.

Review of Literature

According to Raja *et al.* (2012), the macrophyte of *Azolla* is a frond that ranges in length from 1–2.5 cm in *Azolla pinnata* to over 15 cm in *Azolla nilotica*. The frond has a primary rhizome with alternating small leaves and numerous adventitious roots that hang into the water to absorb nutrients. Each leaf has a bilobed structure with a dorsal chlorophyllous lobe and a ventral colorless lobe that aids buoyancy. The inner surface of the leaf cavity contains *Anabaena* filaments embedded in mucilage. Use of *Azolla* as a green manure can increase rice yield by 20–30%.

Maria Enelia Jesus da Silva Lebani *et al.* (2022) investigated the effect of light intensity, nitrogen addition, pH control, and humidity on the growth of *Azolla pinnata*. The study found that higher light intensity and high humidity significantly enhance plant growth, while nitrogen presence in the medium boosts photosynthetic activity.

Yildiz Taylan Köse Şakal and Mustafa (2019) studied *Azolla pinnata* and *Azolla caroliniana* under greenhouse conditions. They observed that *A. pinnata* displayed higher growth rates, pigment content, and essential amino acid concentration compared to *A. caroliniana*. Predominant fatty acids in *A. pinnata* were palmitic, glyceric, and lignoceric acids.

Ahemad M. Tahan and Hamdy Khalifa (2023) conducted experiments in Egypt to test different nutrient solutions on *Azolla pinnata* productivity. Results showed that multiple nutrient solutions significantly increased *Azolla* biomass, tissue NPK content, and water productivity compared to farmer practice, especially during summer.

Materials and Methodology

The laboratory analysis was carried out using standard glassware and plasticware, including beakers, test tubes, Petri dishes, Erlenmeyer flasks, conical centrifuge tubes, and measuring cylinders. All glassware and equipment were sterilized before use to ensure aseptic handling throughout the study.

To assess the growth response of *Azolla pinnata* under different temperature conditions, a plastic tub was first filled with fertile soil to serve as the base substrate. A slurry was then prepared by mixing 50 g of cow dung with super single phosphate, and this mixture was thoroughly incorporated into the soil. Water was added to the tub to establish a suitable aquatic environment for the fern. Healthy *Azolla* culture was subsequently introduced into the prepared medium. The water in the tub was replaced every 8–10 days, and 3 g of phosphate was supplemented during each water change to maintain nutrient availability. The established culture was then divided into three separate experimental setups corresponding to different temperature conditions: 10°C (refrigerator), 25–30 °C (room temperature), and 40 °C (incubator). The growth and color of *Azolla* were observed and recorded over a period of 10 days to evaluate the effects of temperature variation on its performance.

Results and Discussion:

The growth of *Azolla pinnata* was strongly influenced by temperature. The fern exhibited vigorous growth at 10°C and 28°C, while 40°C significantly inhibited its growth. Pigmentation also varied with temperature—plants were dark green at 10°C, green at 28°C, and yellow-green at 40°C, indicating thermal stress and reduced chlorophyll concentration at higher temperatures.

Temperature (°C)	Growth Rate	Color
10°C	High	Dark Green
28°C	High	Green
40°C	Slow	Yellow Green

The results are consistent with previous studies indicating that moderate temperatures and high humidity promote *Azolla* growth. Higher temperatures reduce chlorophyll synthesis and nitrogen-fixation efficiency, leading to slower biomass accumulation.

Figure 1: Preparation of slurry for cultivation of *Azolla pinnata.*

Conclusion:

The study concludes that *Azolla pinnata* achieves optimal growth at 10°C–28°C, while growth and color quality decline at 40°C. The fern's symbiotic relationship with *Anabaena azollae* enables efficient nitrogen fixation, making it an excellent biofertilizer for rice fields and an eco-friendly alternative to synthetic fertilizers. Beyond agriculture, *Azolla* offers potential benefits as a livestock feed, protein supplement, erosion control agent, and natural mosquito larva suppressant.

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ARTIFICIAL INTELLIGENCE AND INTELLIGENT SYSTEMS

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Abstract:

Artificial Intelligence (AI) and Intelligent Systems represent one of the most transformative technological paradigms of the twenty-first century, reshaping scientific discovery, industrial processes, governance structures, and human–machine interaction. This chapter presents a comprehensive examination of AI and intelligent systems, covering their theoretical foundations, computational architectures, learning paradigms, and real-world applications across domains such as healthcare, manufacturing, materials science, energy, and environmental monitoring. Emphasis is placed on data-driven intelligence, autonomous decision-making, and adaptive systems, alongside ethical, safety, and governance considerations. This chapter presents a comprehensive and systematic overview of Artificial Intelligence and Intelligent Systems, tracing their evolution from early symbolic approaches to modern data-driven and autonomous paradigms. It discusses the theoretical foundations of AI, including rational agents, learning paradigms, computational intelligence, and system architectures, which collectively enable machines to perceive, learn, reason, and act in complex environments. Core AI technologies such as machine learning, deep learning, reinforcement learning, and knowledge representation are examined in detail, highlighting their roles in enabling intelligent decision-making and adaptive behavior. The chapter further explores transformative applications across healthcare, manufacturing, materials science, energy, environmental systems, and scientific discovery, demonstrating AI's capacity to accelerate innovation and optimize complex processes. Critical attention is given to explainable, ethical, and trustworthy AI, addressing challenges related to transparency, bias, governance, and societal impact. Finally, the chapter outlines key challenges and future research directions, emphasizing the need for human-centric, responsible, and interdisciplinary approaches to ensure that AI and intelligent systems deliver sustainable scientific and societal benefits.

Keywords: Artificial Intelligence; Intelligent Systems; Machine Learning; Deep Learning; Autonomous Systems; Explainable AI; Ethical AI; Computational Intelligence.

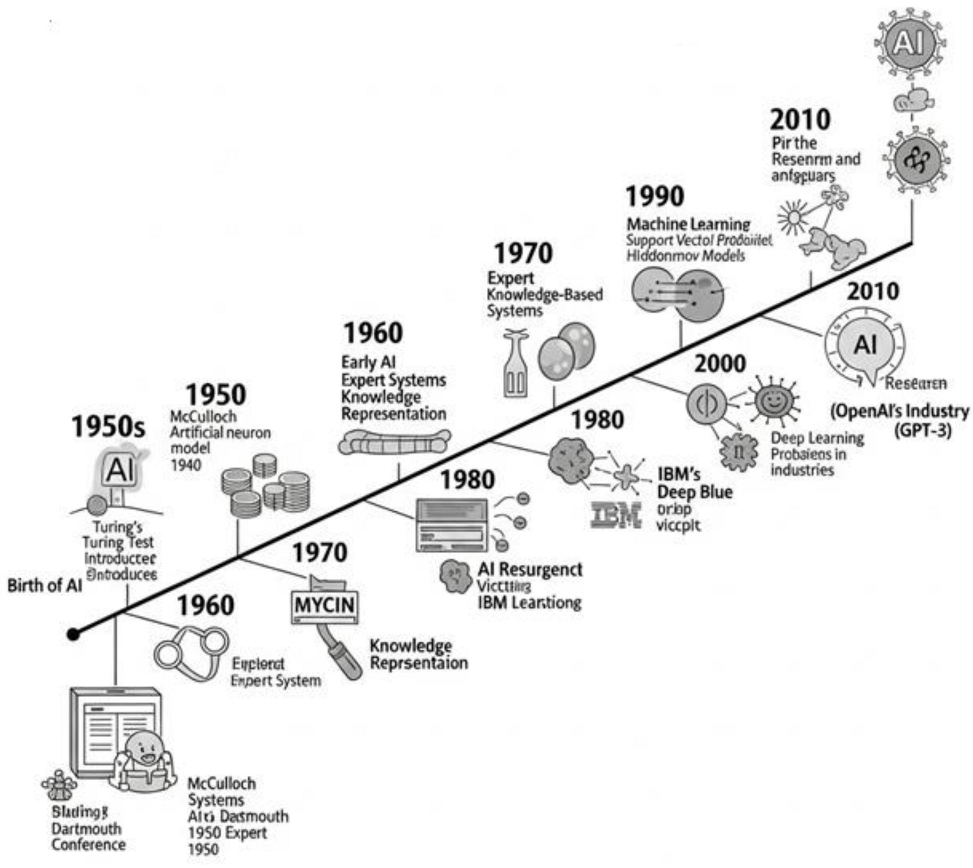
1. Introduction:

Artificial Intelligence (AI) refers to the capability of machines to perform tasks that typically require human intelligence, including perception, reasoning, learning, decision-making, and adaptation. Intelligent systems extend this concept by integrating AI algorithms with sensing, actuation, communication, and control mechanisms, enabling autonomous and context-aware behavior in complex environments. The global economic impact of AI is substantial. According to estimates by PwC, AI could contribute USD 15.7 trillion to the global economy by 2030, with productivity gains accounting for nearly 45% of this value. In scientific research, AI-driven methods have reduced discovery cycles by orders of magnitude, exemplified by deep learning-based protein structure prediction and materials discovery platforms. The integration of Artificial Intelligence, the Internet of Things, and Robotics is redefining the foundations of modern scientific inquiry. Artificial Intelligence (AI) has transcended from being a theoretical concept to a cornerstone of technological advancement. The integration of AI across industries demonstrates its potential to revolutionize processes, systems, and services (Mishra *et al.,* 2024a). The integration of Artificial Intelligence (AI) and Machine Learning (ML) in scientific research is revolutionizing the landscape of knowledge discovery and innovation across diverse fields (Mishra *et al.,* 2024b). Forests are critical to global ecological balance, providing essential ecosystem services, regulating climate, and supporting biodiversity. Managing and protecting these vast ecosystems is a complex task requiring extensive data collection, processing, and analysis. In recent years, artificial intelligence (AI) and machine learning (ML) have emerged as powerful tools to enhance forestry practices. From forest health monitoring and wildfire prediction to species identification and carbon sequestration modelling, AI and ML offer innovative solutions to the multifaceted challenges in forestry (Mishra *et al.,* 2024c).

This emerging synergy creates an interconnected intelligent framework capable of conducting autonomous experimentation, facilitating continuous data collection, adjusting system behavior in real time, and generating predictive scientific insights (Mishra *et al.,* 2025a). Computing 5.0 represents a profound leap in computational paradigms, merging autonomous intelligence, cyber-physical orchestration, neuromorphic architectures, human–AI symbiosis, and large-scale analytical ecosystems. As industries accelerate toward hyper-automation and resilient digital infrastructures, computing 5.0 provides the conceptual and technological backbone required for trustworthy, adaptive, and context-aware intelligent systems (Mishra *et al.,* 2025b). The evolution of materials science in the 21st century is characterized by the unification of chemistry, physics, and computational intelligence into a data-driven, predictive, and sustainable research paradigm. Traditional experimental methodologies are now augmented by computational modeling, machine learning (ML), and high-throughput simulations that enable accelerated discovery and design of novel materials (Mishra *et al.,* 2025c). Artificial Intelligence (AI) is a multidisciplinary field rooted in computer science, mathematics, cognitive science, and engineering (Mishra *et al.,* 2025d). Rapid advances in satellite remote sensing, low-cost Internet of Things (IoT) sensors, and geospatial artificial intelligence (GeoAI), combined with emerging 'digital twin' frameworks, have transformed environmental monitoring from episodic, sparse measurements to dense, near-real-time, multi-scale observational systems (Mishra *et al.,* 2025e).

2. Evolution and Historical Perspective of Artificial Intelligence

The evolution of Artificial Intelligence (AI) reflects a progressive shift from symbolic reasoning to data-driven and learning-based paradigms, shaped by advances in mathematics, computing, and cognitive science. The conceptual foundations of AI emerged in the 1940s and 1950s with seminal contributions such as Alan Turing's notion of machine intelligence and the Turing Test (1950), followed by the Dartmouth Conference in 1956, which formally established AI as a research discipline. Early AI systems were dominated by symbolic or rule-based approaches, including logic programming and expert systems, which aimed to encode human knowledge explicitly but were limited by scalability, brittleness, and knowledge acquisition bottlenecks. The 1980s and 1990s marked a transition toward statistical and probabilistic AI, driven by the availability of digital data and advances in statistical learning theory, leading to the adoption of algorithms such as Bayesian networks, decision trees, and support vector machines.



A major paradigm shift occurred in the 2010s with the resurgence of artificial neural networks and deep learning, enabled by big data, graphical processing units (GPUs), and algorithmic innovations such as backpropagation and convolutional architectures. This era witnessed landmark achievements in computer vision, speech recognition, natural language processing, and strategic decision-making, exemplified by systems like AlphaGo and large-scale transformer models. Today, AI is evolving toward foundation models, autonomous agents, and neuro-symbolic systems, integrating learning, reasoning, and perception, while increasingly influencing scientific discovery, industrial automation, and societal infrastructures. This historical trajectory underscores AI's transformation from narrowly scoped, rule-driven programs to adaptive, data-centric intelligent systems with far-reaching scientific and technological implications. Artificial Intelligence (AI) is rapidly transforming the global landscape of production, learning, and scientific discovery. While its individual applications in industry, education, and research have been widely studied, a comprehensive treatment that integrates these three pillars of knowledge creation and societal development is missing from the academic and professional literature (Mishra *et al.,* 2025f). Artificial Intelligence (AI) and Machine Learning (ML) are revolutionizing the physical sciences by enabling data-driven discovery, accelerating simulations, and uncovering complex patterns in large, multidimensional datasets. This chapter presents a comprehensive exploration of AI and ML applications across various domains including physics, chemistry, earth sciences, astronomy, and materials engineering (Mishra *et al.* 2025g).

The evolution of AI can be broadly categorized into distinct phases:

2.1 Symbolic AI (1950s–1980s)

Symbolic Artificial Intelligence often referred to as "Good Old-Fashioned AI (GOFAI)", dominated the formative decades of AI research from the 1950s through the 1980s and was grounded in the premise that human intelligence could be replicated through explicit symbol manipulation and logical reasoning. Rooted in formal logic, mathematics, and cognitive psychology, symbolic AI systems represented knowledge using symbols, rules, and ontologies, and employed inference mechanisms such as propositional and first-order logic to derive conclusions. Early successes included problem-solving programs like the Logic Theorist and General Problem Solver, as well as knowledge-intensive expert systems such as MYCIN and DENDRAL, which demonstrated expert-level performance in narrow domains like medical diagnosis and chemical analysis. Despite these achievements, symbolic AI faced significant limitations, including poor scalability, brittleness in dynamic environments, and the knowledge acquisition bottleneck, wherein acquiring and maintaining large rule bases required extensive human effort. Moreover, such systems struggled with uncertainty, perception, and learning from raw data, limiting their applicability to real-world, unstructured problems. The constraints of symbolic AI, coupled with increasing computational demands and inflated expectations, contributed to periods of reduced funding known as AI winters, ultimately motivating a paradigm shift toward statistical, probabilistic, and learning-based approaches in subsequent decades.

2.2 Statistical and Machine Learning Era (1990s–2000s)

The statistical and machine learning era of Artificial Intelligence, spanning the 1990s and early 2000s, marked a decisive departure from purely symbolic reasoning toward data-driven and probabilistic approaches to intelligence. This transition was catalyzed by the rapid growth of digital data, advances in statistical learning theory, and increasing computational capacity, which collectively enabled machines to learn patterns directly from empirical observations rather than relying on handcrafted rules. During this period, algorithms such as Bayesian networks, hidden Markov models, decision trees, k-nearest neighbors, and support vector machines (SVMs) became central to AI research and applications, providing mathematically grounded frameworks for handling uncertainty, noise, and variability in real-world data. Machine learning matured into a formal discipline, supported by concepts such as bias–variance trade-off, regularization, and cross-validation, which improved model generalization and robustness. This era also witnessed significant progress in speech recognition, information retrieval, bioinformatics, and financial modeling, where statistical learning methods consistently outperformed symbolic systems. Importantly, the shift toward probabilistic reasoning redefined intelligence as an inferential process under uncertainty, laying the conceptual and algorithmic foundations for modern deep learning and large-scale AI systems that would emerge in the following decade.

2.3 Deep Learning and Data-Driven AI (2010s–Present)

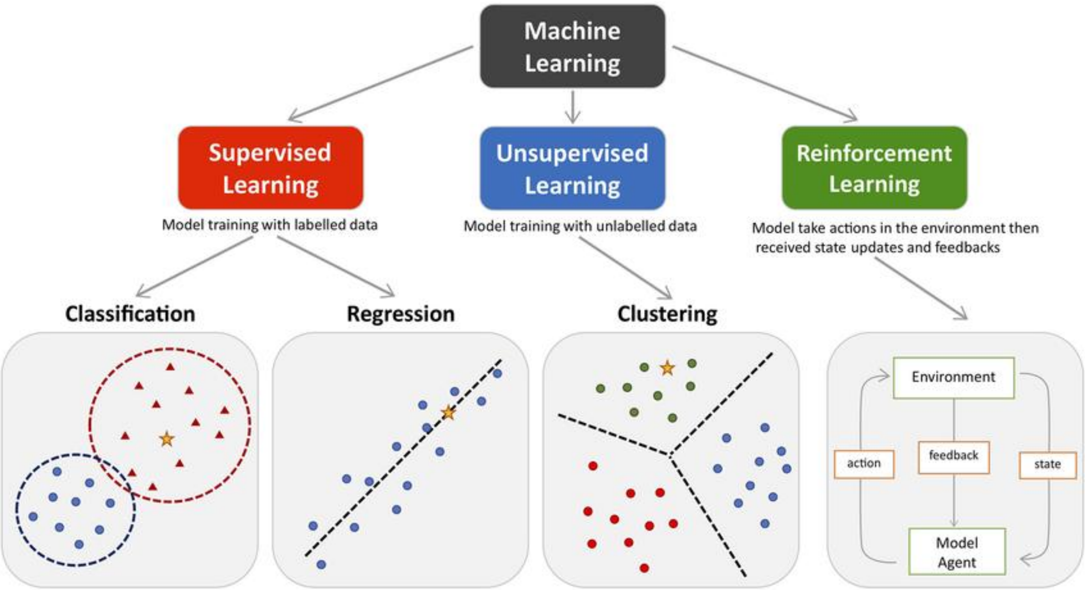
The deep learning and data-driven AI era, emerging prominently in the 2010s, represents the most transformative phase in the history of artificial intelligence, characterized by the ability of machines to learn hierarchical representations directly from large-scale data. This paradigm shift was enabled by the convergence of three critical factors: the exponential growth of labeled and unlabeled datasets, advances in high-performance computing—particularly graphics processing units (GPUs) and tensor processing units (TPUs)—and algorithmic innovations such as efficient backpropagation, rectified linear units (ReLU), and regularization techniques. Landmark breakthroughs, including the success of deep convolutional neural networks in the 2012 ImageNet competition, demonstrated dramatic performance gains in computer vision, catalyzing widespread adoption of deep learning across domains. Subsequently, recurrent neural networks and long short-term memory (LSTM) models advanced sequential data processing, while the introduction of Transformer architectures revolutionized natural language processing by enabling scalable attention-based learning. This period also saw the rise of foundation models and large-scale generative AI systems, trained on trillions of data points and capable of zero-shot and few-shot learning across tasks. Deep learning has since driven unprecedented progress in speech recognition, machine translation, medical imaging, protein structure prediction, and autonomous systems. However, its data- and energy-intensive nature, limited interpretability, and susceptibility to bias have also raised critical concerns, prompting parallel research into explainable, efficient, and responsible AI. Overall, the deep learning era signifies a shift from feature engineering to representation learning, positioning data-driven AI as a central engine of scientific discovery and technological innovation. Deep neural networks, enabled by GPUs and big data, revolutionized pattern recognition, natural language processing, and computer vision. Breakthroughs such as AlexNet (2012) and Transformer architectures (2017) marked a paradigm shift toward representation learning.

3. Theoretical Foundations of AI and Intelligent Systems

The theoretical foundations of Artificial Intelligence (AI) and intelligent systems are rooted in a multidisciplinary convergence of mathematics, computer science, cognitive science, control theory, neuroscience, and philosophy. At the core of AI theory lays the concept of rational agents, formalized through decision theory, where an intelligent system perceives its environment via sensors and selects actions through actuators to maximize an expected utility function under uncertainty. This framework is mathematically supported by probability theory, Bayesian inference, and Markov decision processes (MDPs), which provide principled mechanisms for reasoning, planning, and learning in stochastic environments. Learning theory constitutes another critical pillar, encompassing statistical learning theory, computational learning theory, and information theory, which collectively explain generalization, sample complexity, bias–variance trade-offs, and optimization dynamics in machine learning models. Additionally, optimization theory underpins AI algorithms through gradient-based methods, convex optimization, and heuristic search, enabling efficient parameter estimation in high-dimensional spaces. Intelligent systems further rely on control theory and cybernetics to achieve stability, adaptability, and feedback-driven behavior in dynamic environments, particularly in robotics and autonomous systems. Complementing these mathematical foundations are knowledge representation and reasoning theories, including logic-based systems, ontologies, and graph-based models, which enable structured reasoning and explainability. Together, these theoretical constructs establish AI not merely as a collection of algorithms, but as a rigorous scientific discipline concerned with modeling, learning, and acting intelligently in complex, uncertain, and evolving environments.

3.1 Intelligence and Rational Agents

The concept of intelligence in artificial intelligence is fundamentally formalized through the notion of rational agents, which provides a unifying theoretical framework for designing and analyzing intelligent systems. An intelligent agent is defined as an entity that perceives its environment through sensors and acts upon that environment through actuators, with the objective of maximizing a predefined performance measure or utility function. Rationality, in this context, does not imply omniscience or perfection, but rather the ability to select actions that are expected to yield the best possible outcome given the agent's perceptual limitations, prior knowledge, and available computational resources. This agent-based perspective is grounded in decision theory and expected utility maximization, incorporating probabilistic reasoning to handle uncertainty and incomplete information. The behavior of rational agents is often modeled using Markov decision processes (MDPs) and their extensions, which provide a mathematical framework for sequential decision-making in dynamic and stochastic environments. Furthermore, intelligent agents may exhibit properties such as autonomy, reactivity, proactiveness, and learning, enabling them to adapt their policies over time based on experience. This paradigm has proven foundational across AI subfields, underpinning applications ranging from game-playing systems and recommendation engines to autonomous robots and intelligent control systems, and establishing rational agency as a cornerstone of both theoretical AI and practical intelligent system design.



3.2 Learning Paradigms

Learning paradigms constitute a central theoretical and practical foundation of Artificial Intelligence, defining how intelligent systems acquire knowledge, improve performance, and adapt to new environments through experience. Supervised learning is the most established paradigm, in which models learn a mapping between input–output pairs using labeled datasets; it underpins tasks such as classification, regression, and medical diagnosis, with performance governed by principles such as generalization, bias–variance trade-off, and empirical risk minimization. In contrast, unsupervised learning operates on unlabeled data to uncover latent structures, patterns, or representations, employing techniques such as clustering, dimensionality reduction, and density estimation, which are crucial for exploratory data analysis and feature learning. Reinforcement learning frames learning as a sequential decision-making process, where an agent interacts with an environment and learns optimal policies through reward and punishment signals, relying on concepts from control theory and Markov decision processes; this paradigm is fundamental to robotics, autonomous systems, and adaptive control. More recently, self-supervised learning has emerged as a powerful paradigm that leverages intrinsic data properties to generate supervisory signals, enabling large-scale representation learning without manual annotation and serving as the backbone of modern foundation models. Collectively, these learning paradigms provide complementary mechanisms for enabling intelligence, and their integration within hybrid and multi-modal systems is increasingly recognized as essential for building robust, generalizable, and adaptive intelligent systems.

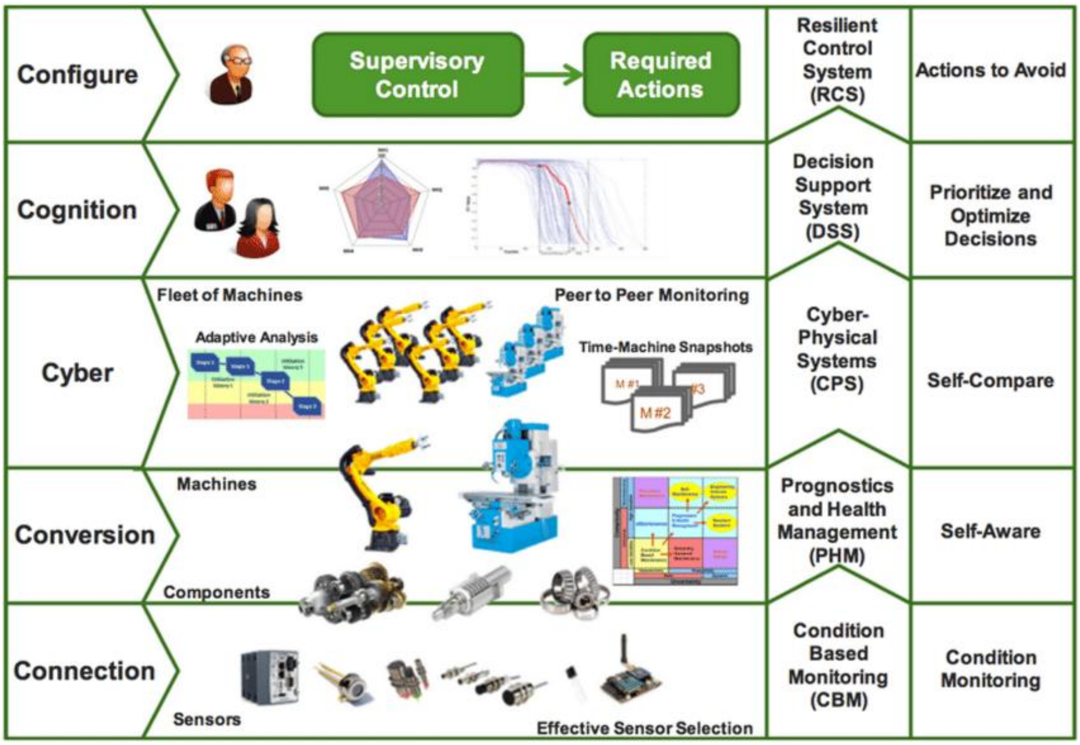
3.3 Computational Intelligence

Computational Intelligence (CI) represents a class of AI methodologies inspired by natural and biological processes, emphasizing adaptability, robustness, and approximate reasoning in complex and uncertain environments. Unlike classical symbolic AI, which relies on explicit logical representations, CI systems are inherently data-driven and capable of learning from experience without requiring precise mathematical models. The core components of computational intelligence include artificial neural networks, which emulate the distributed processing and learning capabilities of biological neurons; fuzzy logic systems, which model human-like reasoning through linguistic variables and degrees of truth to handle vagueness and imprecision; and evolutionary computation, such as genetic algorithms and genetic programming, which employ mechanisms of natural selection and mutation to solve optimization and search problems. Additionally, swarm intelligence, inspired by the collective behavior of social organisms like ants and birds, enables decentralized problem-solving through simple agent interactions. Computational intelligence has proven particularly effective for non-linear, high-dimensional, and multi-objective problems where analytical solutions are intractable, finding extensive applications in control systems, pattern recognition, and optimization, robotics, and decision support systems. By prioritizing adaptability and resilience over exact optimality, computational intelligence complements traditional AI approaches and plays a critical role in the development of intelligent systems capable of operating reliably in real-world, dynamic environments.

4. Architectures of Intelligent Systems

An intelligent system typically consists of the following layers:

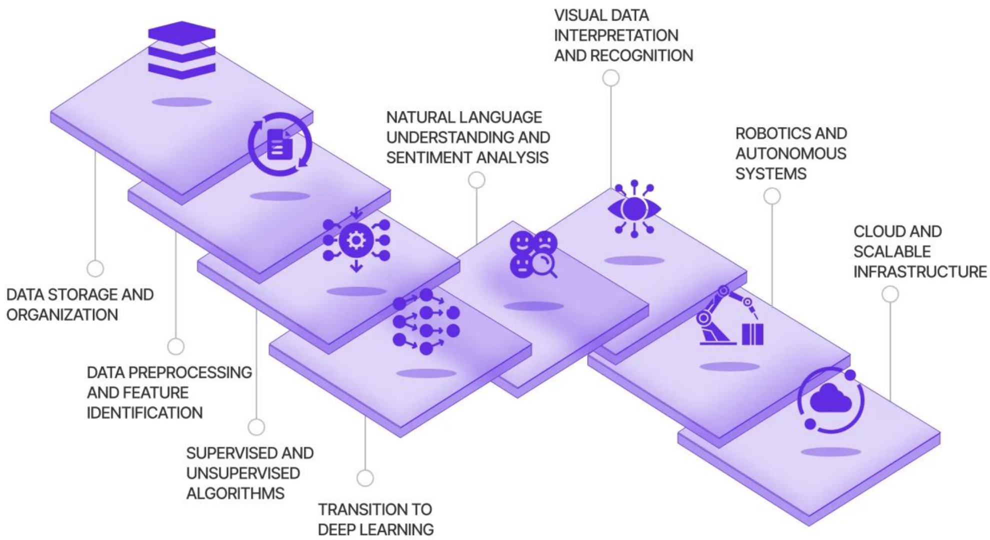
1. Perception Layer – Sensors, computer vision, speech recognition
2. Cognition Layer – Learning, reasoning, and decision-making models
3. Action Layer – Control systems, robotics, actuation
4. Communication Layer – IoT, cloud–edge integration
5. Adaptation Layer – Continuous learning and system optimization



Architectures of intelligent systems define the structural and functional organization through which artificial intelligence capabilities are implemented, integrated, and operationalized in real-world environments. At a conceptual level, an intelligent system is typically designed as a layered or modular architecture, enabling separation of concerns, scalability, and adaptability. The perception layer acquires raw data from sensors and external sources, encompassing signal processing, computer vision, and speech recognition to transform environmental stimuli into machine-interpretable representations. This is followed by the representation and knowledge layer, where features, embeddings, semantic models, or knowledge graphs encode structured and unstructured information. The cognition layer constitutes the core intelligence of the system, integrating machine learning, reasoning, planning, and inference mechanisms to interpret data and generate decisions under uncertainty. Decisions are executed through the action and control layer, which includes actuators, robotics, and control systems that enable interaction with physical or digital environments. A critical component across modern architectures is the feedback and adaptation layer, which supports continuous learning, performance monitoring, and policy refinement through reinforcement and online learning. Contemporary intelligent systems increasingly adopt hybrid and distributed architectures, such as neuro-symbolic systems and cloud–edge–IoT frameworks, to balance learning efficiency, interpretability, latency, and scalability. These architectural principles underpin advanced applications ranging from autonomous vehicles and smart grids to self-driving laboratories and cyber-physical systems, making architecture design a foundational aspect of intelligent system performance and reliability.

5. Core AI Technologies

Core AI technologies constitute the fundamental computational mechanisms that enable intelligent systems to perceive, learn, reason, and act autonomously in complex environments. Machine learning forms the backbone of modern AI, providing algorithms that infer patterns and predictive models from data, with supervised, unsupervised, and reinforcement learning addressing distinct problem settings. Within this domain, deep learning has emerged as a dominant paradigm, leveraging multi-layer neural networks—such as convolutional neural networks for visual perception, recurrent and transformer-based architectures for sequential and language data—to learn hierarchical representations directly from raw inputs. Complementing learning-based approaches, knowledge representation and reasoning technologies enable structured encoding of facts, relationships, and rules through ontologies, semantic networks, and knowledge graphs, supporting logical inference and explainability. Reinforcement learning and sequential decision-making technologies allow agents to learn optimal control policies through interaction with dynamic environments, playing a critical role in robotics, autonomous systems, and resource optimization. Additionally, optimization and search algorithms, including gradient-based methods, evolutionary optimization, and heuristic search, underpin model training, planning, and scheduling tasks. Together, these core AI technologies form an integrated toolkit that supports the development of intelligent systems capable of adaptive learning, contextual reasoning, and autonomous operation across scientific, industrial, and societal applications.



5.1 Machine Learning and Deep Learning

Machine Learning (ML) and Deep Learning (DL) constitute the technological core of contemporary artificial intelligence, enabling systems to automatically learn patterns, representations, and decision rules from data rather than relying on explicit programming. Machine learning encompasses a broad class of algorithms that model relationships between inputs and outputs using statistical and optimization-based techniques, supporting tasks such as classification, regression, clustering, and anomaly detection. Traditional ML methods—including linear models, decision trees, ensemble learning, and support vector machines—are grounded in statistical learning theory and emphasize interpretability, generalization, and computational efficiency. Deep learning represents an advanced subset of machine learning that employs multi-layer artificial neural networks to learn hierarchical and abstract representations directly from raw data. Architectures such as convolutional neural networks (CNNs) have achieved state-of-the-art performance in computer vision, recurrent neural networks (RNNs) and long short-term memory (LSTM) models have advanced sequence modeling, and transformer-based architectures have revolutionized natural language processing through attention mechanisms and parallel computation. The success of deep learning has been driven by the availability of large-scale datasets, high-performance computing infrastructure, and algorithmic innovations in optimization and regularization. While ML and DL have delivered unprecedented accuracy and scalability across domains such as healthcare, autonomous systems, and scientific discovery, they also pose challenges related to data dependency, interpretability, and energy consumption, motivating ongoing research into efficient, explainable, and robust learning paradigms.

5.2 Reinforcement Learning and Autonomous Decision-Making

Reinforcement Learning (RL) provides a foundational framework for autonomous decision-making in artificial intelligence, enabling agents to learn optimal behaviors through direct interaction with dynamic and uncertain environments. In the RL paradigm, an agent observes the state of the environment, selects actions according to a policy, and receives feedback in the form of rewards or penalties, with the objective of maximizing cumulative long-term reward. This sequential decision-making process is formally modeled using Markov Decision Processes (MDPs), which capture state transitions, action spaces, reward functions, and stochastic dynamics. Core RL algorithms include value-based methods such as Q-learning and Deep Q-Networks (DQNs), policy-based approaches such as policy gradients, and hybrid actor–critic architectures that balance stability and learning efficiency. Reinforcement learning has demonstrated remarkable success in complex control and planning tasks, exemplified by superhuman performance in strategic games and real-time decision-making systems. In practical applications, RL underpins autonomous robotics, adaptive traffic control, energy management, recommendation systems, and self-optimizing industrial processes. Despite its potential, RL faces challenges related to sample inefficiency, safety, reward design, and real-world deployment, driving ongoing research into model-based RL, safe exploration, and human-in-the-loop learning to enable reliable and trustworthy autonomous intelligent systems.

5.3 Knowledge Representation and Reasoning

Knowledge Representation and Reasoning (KRR) form a foundational pillar of artificial intelligence concerned with how information about the world is formally encoded, structured, and manipulated to enable intelligent inference and decision-making. Knowledge representation focuses on designing symbolic and sub-symbolic models—such as logic-based formalisms, semantic networks, frames, ontologies, and knowledge graphs—that capture entities, relationships, constraints, and domain rules in a machine-interpretable manner. Reasoning mechanisms operate on these representations to derive new knowledge, draw conclusions, and support explanation through processes such as deductive, inductive, abductive, and probabilistic inference. Classical approaches employ propositional and first-order logic to ensure sound and complete reasoning, while probabilistic frameworks, including Bayesian networks and Markov logic networks, address uncertainty and incomplete information inherent in real-world domains. In modern intelligent systems, KRR is increasingly integrated with machine learning to form neuro-symbolic architectures, combining the adaptability of data-driven learning with the interpretability and logical consistency of symbolic reasoning. Knowledge representation and reasoning play a critical role in explainable AI, decision support systems, semantic web technologies, and intelligent agents, enabling systems not only to make accurate decisions but also to justify and communicate the rationale behind those decisions in complex and high-stakes applications.

6. Applications of AI and Intelligent Systems

Applications of Artificial Intelligence and Intelligent Systems span a wide range of scientific, industrial, and societal domains, reflecting their role as enabling technologies for automation, optimization, and knowledge discovery. In healthcare and biomedical sciences, AI-driven diagnostic systems, medical imaging analysis, and predictive analytics enhance clinical decision-making, enable early disease detection, and support personalized medicine, while intelligent systems streamline hospital operations and patient monitoring. In manufacturing and Industry 4.0, intelligent systems integrate machine learning, robotics, and IoT to enable predictive maintenance, quality inspection, digital twins, and autonomous production lines, significantly improving efficiency, safety, and resource utilization. Energy and environmental systems benefit from AI-based smart grids, renewable energy forecasting, climate modeling, and environmental monitoring, contributing to sustainability and climate resilience. In transportation and autonomous systems, AI enables self-driving vehicles, intelligent traffic management, and logistics optimization through real-time perception, planning, and control. Additionally, AI and intelligent systems play a transformative role in scientific research and engineering, accelerating materials discovery, drug development, and experimental design through data-driven modeling and autonomous laboratories. Beyond technical domains, applications in finance, governance, agriculture, education, and smart cities illustrate the pervasive impact of intelligent systems on economic productivity and societal infrastructure. Collectively, these applications demonstrate how AI-driven intelligence is reshaping decision-making processes and redefining the boundaries of innovation across disciplines.

6.1 Healthcare and Biomedical Sciences

Artificial Intelligence and intelligent systems have emerged as transformative forces in healthcare and biomedical sciences, fundamentally enhancing disease diagnosis, treatment planning, and healthcare delivery. AI-driven medical imaging systems, leveraging deep learning architectures such as convolutional neural networks, achieve diagnostic accuracies comparable to or exceeding those of expert clinicians in areas including radiology, pathology, dermatology, and ophthalmology, enabling early detection of conditions such as cancer, cardiovascular disease, and neurological disorders. In biomedical research, machine learning models analyze high-dimensional genomic, proteomic, and metabolomic data to uncover disease mechanisms and support precision medicine, where treatments are tailored to individual patient profiles. Intelligent systems are also revolutionizing drug discovery and development by accelerating target identification, virtual screening, and toxicity prediction, reducing development timelines from traditional spans of over a decade to a few years. Additionally, AI-powered clinical decision support systems assist physicians by synthesizing patient data, medical literature, and real-time monitoring to improve diagnostic consistency and reduce human error. Beyond clinical care, intelligent systems enable hospital workflow optimization, remote patient monitoring, and telemedicine, contributing to improved healthcare accessibility and efficiency. Despite these advances, challenges related to data privacy, algorithmic bias, interpretability, and regulatory compliance remain critical, underscoring the need for trustworthy, transparent, and ethically governed AI in healthcare applications.

6.2 Manufacturing and Industry 4.0

Artificial Intelligence and intelligent systems are central to the realization of Industry 4.0, driving the transition from conventional automation to smart, connected, and self-optimizing manufacturing ecosystems. By integrating machine learning, robotics, Internet of Things (IoT), and cyber-physical systems, intelligent manufacturing environments enable real-time monitoring, predictive analytics, and autonomous decision-making across the production lifecycle. Predictive maintenance systems, powered by AI-based anomaly detection and time-series analysis, significantly reduce unplanned downtime, extend equipment lifespan, and lower maintenance costs by anticipating failures before they occur. Intelligent quality inspection systems employing computer vision and deep learning enhance defect detection accuracy and consistency beyond manual inspection. Furthermore, digital twins—virtual replicas of physical assets and processes—leverage AI models to simulate, optimize, and adapt manufacturing operations under varying conditions. Autonomous and collaborative robots (cobots) enhance flexibility, safety, and productivity by working alongside human operators. Collectively, these AI-enabled capabilities improve operational efficiency, resource utilization, and supply chain resilience, while supporting mass customization and sustainable manufacturing practices. However, successful deployment also requires addressing challenges related to system interoperability, cybersecurity, workforce reskilling, and ethical adoption, positioning intelligent systems as both a technological and organizational transformation within modern industry.

6.3 Materials Science and Engineering

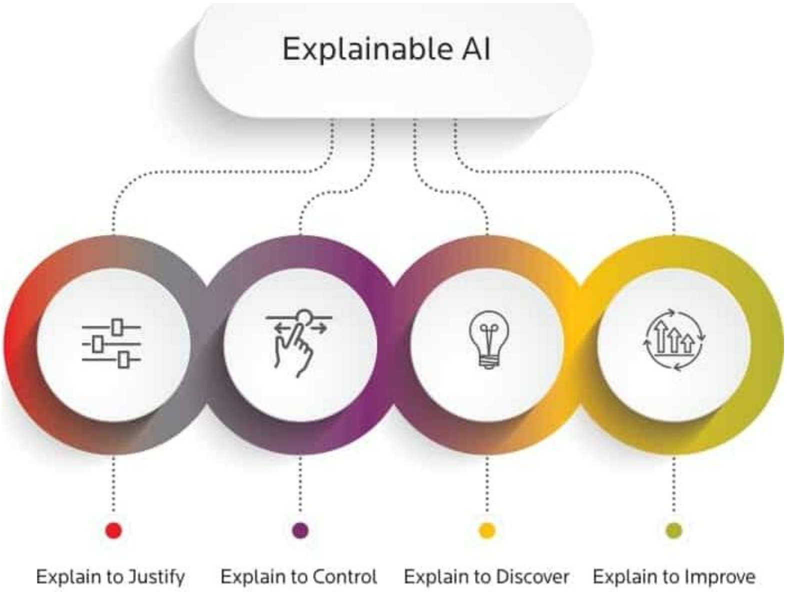
Artificial Intelligence and intelligent systems are increasingly redefining materials science and engineering by transforming traditionally empirical and time-intensive discovery processes into data-driven, predictive, and accelerated workflows. Machine learning models trained on experimental and simulation data enable rapid prediction of material properties—such as mechanical strength, thermal conductivity, electronic band structure, and chemical stability—significantly reducing the reliance on costly trial-and-error experimentation. Materials informatics, which integrates AI with high-throughput computational methods like density functional theory (DFT), facilitates the exploration of vast compositional and structural design spaces, often containing millions of candidate materials. Intelligent systems further support inverse materials design, where desired target properties are specified and AI algorithms identify optimal material compositions and processing conditions to achieve them. Applications span the discovery of advanced alloys, functional ceramics, polymers, nanomaterials, and energy materials for batteries, photovoltaics, and catalysis. Additionally, autonomous experimentation platforms combining AI, robotics, and real-time analytics—often referred to as self-driving laboratories—have demonstrated substantial reductions in discovery timelines, in some cases by an order of magnitude. Despite these advances, challenges related to data quality, model interpretability, and transferability across material classes persist, underscoring the need for standardized datasets, physics-informed learning, and close integration between AI models and fundamental materials science principles.

6.4 Energy and Environmental Systems

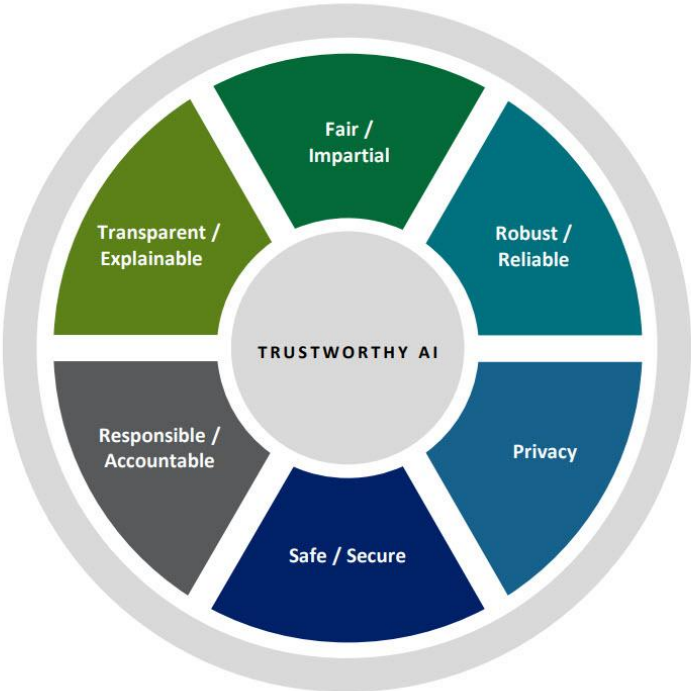
Artificial Intelligence and intelligent systems play a pivotal role in advancing energy efficiency, sustainability, and environmental resilience by enabling data-driven optimization and predictive decision-making across complex natural and engineered systems. In the energy sector, AI-powered smart grids integrate machine learning, real-time sensing, and adaptive control to balance supply and demand, enhance grid stability, and optimize the integration of intermittent renewable energy sources such as solar and wind. Predictive analytics improve energy forecasting accuracy, while intelligent energy management systems can reduce operational losses and enhance overall efficiency. In renewable energy systems, AI supports performance monitoring, fault detection, and optimal placement of generation assets, contributing to higher capacity utilization. Environmental applications include climate modeling, pollution monitoring, biodiversity assessment, and disaster prediction, where AI algorithms analyze large-scale geospatial, remote sensing, and sensor data to identify patterns and anticipate extreme events. Intelligent systems are also applied in water resource management, waste optimization, and carbon capture and storage strategies, supporting evidence-based environmental policy and sustainable development goals. While AI offers significant benefits for energy and environmental systems, challenges related to data availability, model uncertainty, computational cost, and ethical governance must be addressed to ensure reliable, transparent, and environmentally responsible deployment. Ecological risk assessment (ERA) and environmental modelling represent integral components of modern environmental management and decision-making frameworks. ERA provides a scientific basis for evaluating the potential adverse effects of human activities, chemical pollutants, and land-use changes on ecosystems, while environmental models serve as quantitative tools that simulate ecological processes across spatial and temporal scales (Mishra *et al.,* 2025h).

7. Explainable, Ethical, and Trustworthy AI

Explainable, Ethical, and Trustworthy Artificial Intelligence has emerged as a critical research and governance priority as AI systems increasingly influence high-stakes decisions in healthcare, finance, governance, and critical infrastructure.



Explainable AI (XAI) focuses on developing methods that make the behavior and outputs of complex AI models—particularly deep learning systems—transparent and interpretable to human users, employing techniques such as feature attribution, rule extraction, surrogate models, and counterfactual explanations. Explainability is essential for building user trust, enabling debugging, ensuring regulatory compliance, and supporting accountability. Beyond transparency, ethical AI addresses normative concerns related to fairness, bias, privacy, consent, and the prevention of harm, recognizing that AI systems can inadvertently reinforce social inequities or enable surveillance and discrimination if not carefully designed and governed. Trustworthy AI further encompasses robustness, reliability, safety, and security, ensuring that systems perform consistently under uncertainty, resist adversarial manipulation, and incorporate meaningful human oversight. International frameworks and regulations, including risk-based AI governance models, emphasize principles such as transparency, accountability, human-centric design, and proportionality. Collectively, explainability, ethics, and trustworthiness form an integrated foundation for responsible AI deployment, ensuring that intelligent systems not only achieve high performance but also align with societal values, legal standards, and long-term public interest.



7.1 Explainable AI (XAI)

Explainable Artificial Intelligence (XAI) addresses the critical need for transparency and interpretability in AI systems, particularly those based on complex and opaque models such as deep neural networks. As AI-driven decisions increasingly affect high-stakes domains—including healthcare, finance, legal systems, and critical infrastructure—understanding how and why a model arrives at a particular output becomes essential for trust, accountability, and regulatory compliance. XAI encompasses a range of techniques designed to provide human-interpretable explanations of model behavior, including feature attribution methods (e.g., SHAP and LIME), model-agnostic surrogate models, rule extraction, attention visualization, and counterfactual explanations that illustrate how input changes could alter outcomes. From a theoretical perspective, XAI bridges machine learning with cognitive science and human–computer interaction by aligning explanations with human reasoning processes. Practically, explainability supports model validation, bias detection, error analysis, and user confidence, enabling stakeholders to assess reliability and fairness. However, challenges remain in balancing explainability with predictive performance, standardizing evaluation metrics for explanations, and ensuring that explanations are faithful rather than merely plausible. Consequently, XAI is increasingly viewed not as an optional enhancement but as a foundational requirement for the deployment of trustworthy and responsible intelligent systems.

7.2 Ethical and Societal Concerns

The rapid proliferation of artificial intelligence and intelligent systems has given rise to significant ethical and societal concerns, underscoring the need for responsible design, deployment, and governance. One of the foremost issues is algorithmic bias, where AI systems trained on historical or unrepresentative data may reinforce existing social inequalities, leading to unfair outcomes in areas such as hiring, credit allocation, healthcare access, and criminal justice. Privacy and data protection constitute another critical challenge, as AI systems often rely on large-scale personal and behavioral data, raising concerns about surveillance, consent, and misuse of sensitive information. The increasing automation enabled by AI has also intensified debates around labor displacement and workforce transformation, with certain job categories at risk of obsolescence while new skill-intensive roles emerge, necessitating large-scale reskilling and educational reform. Furthermore, the deployment of autonomous and decision-making systems introduces questions of accountability and liability, particularly when AI-driven actions result in harm or unintended consequences. Broader societal implications include the concentration of technological power, digital divides between regions and communities, and the ethical risks associated with military and surveillance applications. Addressing these concerns requires interdisciplinary collaboration, transparent governance frameworks, inclusive policy-making, and the alignment of AI development with human values, social justice, and long-term societal well-being. Key issues include algorithmic bias, privacy violations, surveillance risks, and workforce displacement. According to the World Economic Forum, 85 million jobs may be displaced by AI by 2025, while 97 million new roles may emerge.

7.3 Governance and Regulation

Governance and regulation of artificial intelligence are essential to ensure that AI and intelligent systems are developed and deployed in a manner that is safe, ethical, transparent, and aligned with societal values. As AI technologies increasingly influence critical sectors such as healthcare, finance, transportation, and public administration, governments and international organizations have moved toward risk-based regulatory frameworks that classify AI systems according to their potential impact and associated harms. These frameworks emphasize principles such as accountability, transparency, human oversight, fairness, and robustness, requiring developers and deployers to assess and mitigate risks throughout the AI lifecycle. Regulatory approaches also address issues of data protection, model accountability, safety certification, and auditability, often in alignment with existing legal instruments related to privacy and consumer protection. Beyond formal regulation, AI governance encompasses standards development, ethical guidelines, institutional oversight mechanisms, and multi-stakeholder participation involving academia, industry, civil society, and policymakers. Effective governance must strike a balance between fostering innovation and preventing misuse or harm, ensuring that AI systems remain human-centric and socially beneficial. As AI continues to evolve rapidly, adaptive, internationally coordinated regulatory strategies will be crucial for managing cross-border impacts and maintaining public trust in intelligent technologies.

8. Intelligent Systems in Scientific Discovery

Intelligent systems are increasingly transforming scientific discovery by augmenting human reasoning with data-driven learning, automated experimentation, and adaptive decision-making, thereby redefining traditional research workflows. By integrating artificial intelligence with high-performance computing, robotics, and advanced sensing technologies, intelligent systems enable the automated analysis of massive and complex datasets, rapid hypothesis generation, and optimized experimental design. In domains such as materials science, chemistry, biology, and physics, AI models predict properties, identify patterns, and guide experiments toward promising regions of vast search spaces, significantly reducing time and cost compared to conventional trial-and-error approaches. The emergence of self-driving laboratories, which combine machine learning algorithms, robotic experimentation, and real-time feedback loops, exemplifies this paradigm shift, with reported acceleration factors of several times over manual experimentation. Intelligent systems also enhance simulation-based discovery through surrogate modeling and uncertainty quantification, allowing researchers to explore complex phenomena with greater efficiency and precision. While these advances position AI as a powerful "co-scientist," challenges related to data quality, model interpretability, and integration with domain knowledge remain critical, highlighting the importance of human–AI collaboration in ensuring that intelligent systems advance scientific understanding in a reliable and responsible manner. AI is increasingly viewed as a co-scientist, capable of hypothesis generation, experiment planning, and data interpretation. Autonomous laboratories integrating AI, robotics, and IoT have demonstrated discovery acceleration factors of 5–10× compared to traditional methods.

9. Challenges and Limitations

Despite the remarkable progress of artificial intelligence and intelligent systems, several fundamental challenges and limitations continue to constrain their reliability, scalability, and broader societal adoption. A primary technical challenge is the dependence on large volumes of high-quality data, as many AI models, particularly deep learning systems, exhibit degraded performance when trained on sparse, biased, or noisy datasets. Closely related is the issue of generalization and robustness, where models that perform well in controlled environments may fail under real-world distribution shifts or adversarial conditions. The lack of interpretability and causal understanding in many data-driven models further limits trust and hamper deployment in high-stakes applications. From a computational perspective, AI systems often require substantial energy and hardware resources, raising concerns about sustainability and environmental impact. In autonomous and safety-critical systems, challenges related to alignment, verification, and validation persist, as unintended behaviors may emerge from complex learning dynamics. Additionally, organizational and societal barriers—including skills gaps, integration with legacy systems, ethical risks, and regulatory uncertainty—can impede effective implementation. Addressing these challenges requires advances in efficient and explainable algorithms, robust evaluation methodologies, interdisciplinary collaboration, and governance frameworks that balance innovation with accountability and societal well-being.

10. Future Research Directions

Future research in artificial intelligence and intelligent systems is expected to be shaped by the pursuit of more general, robust, and human-aligned forms of intelligence, moving beyond narrow task-specific solutions. A key direction involves the development of Artificial General Intelligence (AGI) and scalable learning frameworks, informed by empirical scaling laws and improved training efficiency, to enable broader transferability and reasoning capabilities across domains. Neuro-symbolic and causal AI represent another critical frontier, aiming to integrate data-driven learning with symbolic reasoning and causal inference to enhance interpretability, generalization, and decision reliability. Research into embodied intelligence and human–AI collaboration seeks to create systems that learn through physical and social interaction, enabling safer and more intuitive integration with human environments. Additionally, advances in efficient, sustainable, and federated learning are essential to reduce energy consumption, protect data privacy, and support decentralized intelligence at the edge. AI for scientific discovery, sustainability, and climate resilience is poised to play a central role in addressing global challenges, while parallel efforts in AI safety, alignment, and governance will be necessary to ensure long-term societal benefit. Collectively, these research directions underscore a shift toward convergent, interdisciplinary AI paradigms that emphasize responsibility, inclusivity, and transformative scientific impact.

Conclusion:

Artificial Intelligence and Intelligent Systems have evolved into foundational technologies that are reshaping scientific research, industrial practice, and societal infrastructure. From their theoretical roots in rational agents and learning paradigms to their realization in data-driven architectures and autonomous decision-making systems, AI technologies have demonstrated unprecedented capabilities in perception, prediction, and optimization across diverse domains. Applications in healthcare, manufacturing, materials science, energy, and environmental systems highlight AI's potential to accelerate discovery, enhance efficiency, and address complex global challenges. However, the transformative power of intelligent systems is accompanied by significant technical, ethical, and governance-related challenges, including issues of interpretability, robustness, fairness, and sustainability. Addressing these concerns requires a holistic approach that integrates advances in explainable and trustworthy AI with inclusive regulatory frameworks and interdisciplinary collaboration. Looking forward, the future of AI lies not merely in increasing computational scale, but in developing human-centric, responsible, and scientifically grounded intelligent systems that augment human capabilities while aligning with societal values. By balancing innovation with accountability, AI and intelligent systems can serve as enduring catalysts for sustainable technological progress and collective well-being.

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AI-DRIVEN BEHAVIORAL BIOMETRICS FOR CONTINUOUS USER AUTHENTICATION

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Abstract:

Traditional authentication mechanisms such as passwords and one-time verification methods are increasingly vulnerable to credential theft, replay attacks, and unauthorized access. To address these limitations, continuous user authentication based on behavioral biometrics has emerged as a promising security paradigm. This research presents an AI-driven framework for continuous user authentication that leverages behavioral patterns including keystroke dynamics, mouse movement, touch interaction, and usage rhythm to verify user identity in real time. Advanced machine learning and deep learning models are employed to learn unique behavioral signatures while adapting to natural variations in user behavior. The proposed system operates unobtrusively in the background, enabling persistent authentication without disrupting user experience. Experimental evaluation using benchmark and real-world behavioral datasets demonstrates improved authentication accuracy, reduced false acceptance rates, and enhanced resilience against impersonation attacks compared to traditional static authentication methods. Additionally, privacy-preserving techniques are incorporated to ensure secure handling of sensitive behavioral data. The results indicate that AI-driven behavioral biometrics can significantly strengthen access control mechanisms and provide a scalable, user-friendly solution for securing modern digital systems.

1. Introduction:

The rapid expansion of digital services, remote work environments, and online transactions has intensified the need for robust user authentication mechanisms. Traditional authentication methods such as passwords, PINs, and one-time verification techniques provide only point-in-time security and are increasingly vulnerable to threats including credential theft, phishing attacks, brute-force attempts, and session hijacking. Once initial access is granted, these static mechanisms fail to continuously verify the legitimacy of the user, creating significant security gaps. Continuous user authentication has emerged as an advanced security paradigm designed to address these limitations by persistently validating user identity throughout an active session. Behavioral biometrics, which rely on patterns of human interaction rather than physical traits, have proven particularly suitable for continuous authentication. These include keystroke dynamics, mouse movement patterns, touchscreen gestures, application usage behavior, and interaction rhythms. Such behavioral characteristics are difficult to replicate and evolve naturally over time, making them resilient against impersonation attacks.

Recent advancements in artificial intelligence (AI) and machine learning have further enhanced the feasibility of behavioral biometric systems. AI-driven models can learn complex behavioral patterns, adapt to intra-user variability, and detect anomalies in real time. This paper explores an AI-driven framework for continuous user authentication based on behavioral biometrics, emphasizing system architecture, feature extraction, learning models, security advantages, and implementation challenges.

2. Background and Related Work

Behavioral biometrics differ fundamentally from traditional physiological biometrics such as fingerprints or facial recognition. While physiological traits are relatively static and often require explicit user interaction, behavioral traits are dynamic, passive, and continuously observable during normal system use. Early research in behavioral biometrics focused primarily on keystroke dynamics, demonstrating that typing rhythm could uniquely identify users. Subsequent studies expanded the scope to include mouse dynamics, touchscreen behavior, and gait analysis. With the growth of mobile computing, touch-based behavioral features such as swipe speed, pressure, and gesture patterns have gained prominence. However, early systems relied on rule-based or statistical classifiers, which struggled with scalability and adaptability. The introduction of machine learning techniques, including support vector machines, random forests, and neural networks, significantly improved authentication accuracy. More recent work has explored deep learning architectures such as recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and convolutional neural networks (CNNs) to capture temporal dependencies in behavioral data. Despite these advancements, challenges related to privacy, behavioral drift, and computational overhead remain active research concerns.

3. Behavioral Biometrics for Continuous Authentication

3.1 Types of Behavioral Biometrics

Behavioral biometrics encompass a diverse set of user interaction patterns that reflect how individuals naturally interact with digital systems over time. One of the most extensively studied modalities is keystroke dynamics, which examines temporal characteristics of typing behavior such as key press duration, inter-key latency, typing speed, and rhythm. These timing-based features capture subconscious motor patterns that are highly individual-specific and remain relatively stable under normal usage conditions, making them valuable for continuous authentication. Mouse dynamics provide another rich source of behavioral information by analyzing cursor movement patterns during system interaction. Features such as movement speed, acceleration, click frequency, dwell time, scrolling behavior, and trajectory curvature are extracted to characterize user behavior. These parameters reflect fine-grained motor control and decision-making habits, enabling effective differentiation between legitimate users and impostors, particularly in desktop and workstation environments.

In mobile and touch-enabled devices, touchscreen behavioral biometrics play a critical role in continuous authentication. Touch-based features include swipe velocity, gesture orientation, pressure intensity, contact area, and interaction duration. These features capture the unique manner in which users interact with touch interfaces, influenced by factors such as hand posture, device handling style, and motor coordination. The widespread adoption of smartphones and tablets has significantly increased the relevance of touchscreen biometrics in real-world authentication systems. Beyond low-level interaction metrics, higher-level behavioral traits offer valuable contextual information for identity verification. These traits include application usage frequency, navigation paths, interaction sequences, task-switching behavior, and habitual response patterns. Such behavioral cues reflect cognitive preferences and usage habits that are difficult for adversaries to replicate consistently. Incorporating these higher-level features allows authentication systems to model user behavior more holistically.

The integration of multiple behavioral modalities into a multimodal authentication framework significantly enhances system robustness. By combining keystroke, mouse, touch, and contextual behavioral features, the system can compensate for the weaknesses of individual modalities and reduce false acceptance and rejection rates. Multimodal behavioral biometric systems are also more resilient to spoofing and replay attacks, as successfully mimicking multiple behavioral traits simultaneously is considerably more challenging for attackers. This multimodal approach therefore strengthens both security and reliability in continuous user authentication systems.

3.2 Advantages of Behavioral Biometrics

Behavioral biometrics offer several significant advantages over traditional authentication mechanisms such as passwords, PINs, and one-time verification codes. One of the most notable benefits is their transparent and unobtrusive operation. Behavioral biometric systems function passively in the background by continuously monitoring user interactions, eliminating the need for explicit authentication actions after initial access. This seamless operation ensures that security measures do not disrupt workflow or degrade the overall user experience. Another key advantage is the provision of continuous authentication throughout an active session. Unlike conventional methods that verify identity only at the point of login, behavioral biometrics continuously assess user behavior in real time. This capability allows systems to promptly detect anomalies or unauthorized access attempts, such as session hijacking or credential compromise, and respond by triggering re-authentication or terminating the session. As a result, security coverage is extended beyond initial access, significantly reducing the window of vulnerability. Behavioral biometrics are also inherently resistant to impersonation and spoofing attacks. The behavioral traits used for authentication—such as typing rhythm, mouse movement patterns, and touchscreen interactions—are shaped by subconscious motor skills and cognitive habits. These patterns are difficult for attackers to replicate consistently, even if they possess knowledge of the legitimate user's credentials. This characteristic enhances the robustness of authentication systems against both automated attacks and human impersonation.

Furthermore, behavioral biometric authentication improves usability and user convenience by eliminating reliance on complex credentials that must be remembered, frequently changed, or securely stored. Users are no longer burdened with managing passwords, reducing the likelihood of insecure practices such as password reuse or weak password selection. By combining high usability with strong security guarantees, behavioral biometrics strike an effective balance between protection and practicality, making them well suited for modern, user-centric digital environments.

4. AI-Driven Authentication Framework

4.1 System Architecture

The proposed AI-driven continuous authentication framework is structured around four fundamental components: data acquisition, feature extraction, behavioralmodeling, and decision-making, each playing a critical role in ensuring accurate, adaptive, and real-time user authentication. This modular architecture enables scalability, flexibility, and seamless integration with existing digital systems. The data acquisition component is responsible for the passive and continuous collection of user interaction data through system sensors and input devices. These sources include keyboards, mice, touchscreens, and application-level logs, depending on the operating environment. Data collection is performed unobtrusively during normal system usage, ensuring that authentication occurs transparently without requiring additional user interaction. The acquired raw data captures fine-grained temporal and spatial characteristics of user behavior, forming the foundation for subsequent analysis.

In the feature extraction stage, relevant behavioral attributes are derived from the raw interaction data. These features include timing-based metrics, motion characteristics, gesture parameters, and contextual usage patterns. To improve model reliability, preprocessing techniques such as noise filtering, normalization, and outlier removal are applied to mitigate the effects of hardware differences, environmental factors, and natural behavioral variability. Feature normalization ensures consistency across sessions and users, enabling accurate comparison and learning. The behavioral modeling component employs machine learning and deep learning algorithms to learn distinctive behavioral profiles for individual users. During an initial enrollment or training phase, the system establishes baseline behavioral patterns by analyzing historical interaction data. These models are designed to capture both stable behavioral traits and acceptable variations over time. Adaptive learning mechanisms allow the models to update incrementally, accommodating gradual changes in user behavior while maintaining resistance to unauthorized access attempts.

The decision-making module performs continuous evaluation of incoming behavioral data by comparing it against the learned user models. Authentication confidence scores are computed in real time based on similarity measures or classification outputs. These scores are assessed against predefined security thresholds to determine the authentication state. When confidence levels fall below acceptable limits, the system can initiate appropriate security responses, such as step-up authentication, user alerts, or session termination. This dynamic decision-making process ensures persistent security while minimizing false rejections.

Together, these components form a robust and intelligent continuous authentication framework that leverages AI to balance security, adaptability, and user convenience. The architecture supports real-time identity verification, rapid threat detection, and scalable deployment across diverse computing environments.

4.2 Machine Learning and Deep Learning Models

A wide range of artificial intelligence models can be employed to support behavioral biometric authentication, each offering distinct advantages in terms of accuracy, computational efficiency, and interpretability. Traditional machine learning algorithms, such as support vector machines (SVMs), k-nearest neighbors (k-NN), decision trees, and ensemble classifiers including random forests and gradient boosting methods, have been widely used due to their relatively low computational overhead and ease of deployment. These models are particularly effective when working with well-defined, handcrafted behavioral features and offer a degree of interpretability that facilitates system tuning and security analysis. In contrast, deep learning models are well suited for capturing the complex, nonlinear, and temporal nature of behavioral biometric data. Recurrent neural network architectures, especially long short-term memory (LSTM) and gated recurrent unit (GRU) networks, excel at modeling sequential interaction patterns such as keystroke timings, mouse trajectories, and touch gestures. More recently, transformer-based architectures have gained attention due to their ability to model long-range dependencies and contextual relationships in behavioral sequences without relying on recurrence. These models can automatically learn discriminative features from raw or minimally processed data, reducing the need for extensive manual feature engineering.

To address the dynamic nature of human behavior, adaptive learning mechanisms are incorporated into behavioral biometric systems. User behavior naturally evolves over time due to factors such as fatigue, emotional state, device changes, or environmental conditions. Adaptive models update user profiles incrementally using trusted interaction data, allowing the system to remain accurate while avoiding overfitting or vulnerability to adversarial manipulation. Controlled adaptation strategies, such as confidence-based updates and sliding window learning, help maintain a balance between adaptability and security. Furthermore, ensemble learning approaches that combine multiple models or modalities significantly enhance system robustness and reliability. By aggregating predictions from diverse classifiers or integrating outputs from different behavioral modalities, ensemble systems can compensate for weaknesses in individual models and reduce error rates. This multi-model strategy improves resilience against spoofing attempts, noisy data, and partial behavioral changes, resulting in more stable and accurate continuous authentication performance. Overall, the strategic integration of traditional machine learning, deep learning, adaptive mechanisms, and ensemble techniques enables the development of effective, scalable, and secure AI-driven behavioral biometric authentication systems capable of operating reliably in real-world environments.

5. Security Analysis and Performance Evaluation

AI-driven behavioral biometric systems provide strong resistance against common authentication attacks. Since authentication is continuous, session hijacking attempts can be detected when behavioral patterns deviate from the legitimate user profile. The system can trigger re-authentication or session termination in response to anomalies. Performance evaluation typically considers metrics such as authentication accuracy, false acceptance rate, false rejection rate, and response time. Experimental studies reported in the literature indicate that AI-based behavioral authentication systems outperform static methods and single-modality biometric systems, particularly when multimodal features are used.

6. Privacy and Ethical Considerations

Despite their advantages, behavioral biometric systems raise important privacy and ethical concerns. Behavioral data may reveal sensitive information about user habits and preferences. To address these issues, privacy-preserving techniques such as data anonymization, on-device processing, and encrypted storage should be employed. Federated learning approaches can further enhance privacy by allowing models to be trained locally on user devices without sharing raw data. Transparent data usage policies and user consent mechanisms are essential to ensure ethical deployment.

7. Applications and Use Cases

AI-driven behavioral biometric authentication systems demonstrate wide applicability across diverse application domains due to their unobtrusive nature, adaptability, and continuous security capabilities. In enterprise environments, particularly those supporting remote and hybrid work models, behavioral biometrics can significantly enhance access control mechanisms. By continuously verifying employee identity during active sessions, organizations can mitigate risks associated with compromised credentials, insider threats, and unauthorized access to sensitive corporate resources, even when users operate outside traditional network perimeters. In the financial services sector, continuous authentication based on behavioral biometrics plays a critical role in fraud prevention and risk management. Online banking platforms, digital payment systems, and e-commerce applications can leverage behavioral patterns to detect anomalous activity in real time, such as account takeover attempts or unauthorized fund transfers. Unlike static authentication methods that verify identity only at login, behavioral biometrics enable persistent monitoring throughout the transaction lifecycle, allowing rapid intervention before financial losses occur. Mobile devices represent another key area where behavioral biometrics are highly effective. Smartphones and tablets store extensive personal and professional information, making them attractive targets for attackers. Touch-based behavioral authentication provides continuous protection without requiring repeated user interaction, enhancing both security and user experience. This approach is particularly valuable in scenarios involving device sharing, loss, or theft.

In healthcare systems, behavioral biometric authentication can safeguard access to electronic health records and clinical applications while minimizing disruption to healthcare professionals. Continuous verification ensures that only authorized personnel access sensitive patient data, supporting compliance with privacy regulations and reducing the risk of data breaches. Similarly, e-learning platforms benefit from persistent user verification by preventing impersonation during online assessments, protecting intellectual property, and ensuring the integrity of digital learning environments.

The integration of behavioral biometrics within zero-trust security architectures further strengthens overall system resilience. Zero-trust frameworks operate on the principle that no user or device should be inherently trusted, regardless of location or prior authentication. By continuously validating user identity and device behavior, behavioral biometrics provide a dynamic trust assessment mechanism that aligns naturally with zero-trust principles. This continuous validation enhances threat detection, reduces attack surfaces, and supports adaptive access control policies, making behavioral biometrics a foundational component of next-generation secure systems.

8. Challenges and Future Research Directions

Several challenges must be addressed to enable widespread adoption of behavioral biometric authentication. Behavioral drift, where user behavior changes over time, can affect model accuracy. Balancing adaptability with security remains a key research challenge. Future research should explore explainable AI models to improve transparency and trust, as well as adversarial robustness against spoofing attempts. The integration of behavioral biometrics with multimodal authentication and emerging technologies such as edge computing and digital identity frameworks represents promising research directions.

Conclusion:

AI-driven behavioral biometrics represent a robust and user-centric approach to continuous user authentication in contemporary digital environments characterized by increasing complexity and persistent security threats. By harnessing advanced machine learning and deep learning techniques, these systems are capable of learning intricate behavioral patterns and adapting to natural variations in user interactions. This intelligence enables persistent identity verification throughout active sessions, effectively addressing the limitations of traditional point-in-time authentication mechanisms. A key strength of AI-driven behavioral authentication lies in its ability to balance strong security with enhanced usability. Unlike conventional methods that require repeated credential input or explicit user actions, behavioralbiometric systems operate transparently in the background, minimizing friction while maintaining continuous protection. Their resilience against evolving cyber threats—such as credential theft, session hijacking, and impersonation attacks—stems from the difficulty of accurately replicating complex behavioral patterns over time. Despite these advantages, several challenges must be addressed to ensure reliable and ethical deployment. Issues related to user privacy, model scalability, and behavioral variability remain significant considerations. Behavioral data can be sensitive in nature, necessitating robust privacy-preserving mechanisms, secure data handling practices, and transparent user consent frameworks. Additionally, maintaining authentication accuracy in the presence of behavioral drift requires adaptive learning strategies that balance flexibility with resistance to adversarial exploitation.

Looking forward, ongoing advancements in artificial intelligence, edge computing, and secure system design are expected to further enhance the feasibility and effectiveness of behavioral biometric authentication. The integration of explainable AI, federated learning, and zero-trust security principles will contribute to more transparent, scalable, and privacy-aware systems. As digital ecosystems continue to expand, the continued development of ethical, adaptive, and privacy-conscious behavioral authentication solutions will play a critical role in strengthening digital trust and shaping the future landscape of cybersecurity.

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SELF-SUPERVISED LEARNING FOR LOW-RESOURCE NATURAL LANGUAGE PROCESSING

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Abstract:

Natural language processing (NLP) systems typically rely on large volumes of annotated data, which are unavailable for many low-resource languages and domain-specific applications. This limitation significantly hinders the development of accurate and inclusive language technologies. Self-supervised learning has recently emerged as a powerful paradigm for overcoming data scarcity by enabling models to learn rich linguistic representations from unlabeled text. This paper investigates the application of self-supervised learning techniques to low-resource NLP tasks, focusing on representation learning, transferability, and task adaptation. Pretraining strategies based on masked language modeling and contrastive objectives are explored to capture syntactic and semantic patterns without manual annotation. The learned representations are evaluated on downstream tasks such as text classification, named entity recognition, and part-of-speech tagging using limited labeled data. Experimental results demonstrate that self-supervised pretrained models significantly outperform conventional supervised approaches in low-resource settings while requiring fewer labeled samples. The findings highlight the potential of self-supervised learning to reduce data dependency, improve linguistic generalization, and support the development of NLP systems for underrepresented languages and domains.

1. Introduction:

Natural Language Processing (NLP) has witnessed remarkable progress over the past decade, largely driven by deep learning models trained on massive labeled datasets. However, this success has been unevenly distributed across languages and application domains. While high-resource languages benefit from abundant annotated corpora, many languages and specialized domains remain low-resource due to the high cost, time, and expertise required for data annotation. This imbalance has limited the reach of NLP technologies and raised concerns about inclusivity and fairness in language technologies. Low-resource NLP refers to scenarios where only limited labeled data is available for training models. Traditional supervised learning approaches struggle in such settings, often resulting in poor generalization and unreliable performance. As a result, there is a growing need for learning paradigms that can effectively exploit unlabeled data, which is typically more accessible even for low-resource languages.

Self-supervised learning has emerged as a promising solution to this challenge. By designing surrogate learning objectives that do not require human annotation, self-supervised methods enable models to learn meaningful linguistic representations directly from raw text. These representations can then be adapted to downstream NLP tasks using minimal labeled data. This paper examines the role of self-supervised learning in low-resource NLP, focusing on its methodologies, benefits, challenges, and future potential.

2. Background and Motivation

The majority of contemporary natural language processing (NLP) systems are built upon supervised learning paradigms, in which models are trained using large volumes of annotated data tailored to specific tasks such as text classification, named entity recognition, machine translation, and syntactic parsing. While this approach has led to impressive performance gains in high-resource languages, it poses significant challenges in low-resource settings. The limited availability of labeled data in such contexts often results in model overfitting, restricted vocabulary coverage, and inadequate representation of linguistic variability, including morphological richness, dialectal differences, and contextual nuances.To address these limitations, earlier research in low-resource NLP explored alternative strategies such as rule-based systems, which relied on handcrafted linguistic rules and domain expertise, and transfer learning techniques that leveraged annotated resources from related high-resource languages. Semi-supervised learning approaches attempted to combine small labeled datasets with larger amounts of unlabeled text to improve model generalization. Although these methods provided incremental improvements, they frequently required extensive linguistic knowledge, language-specific resources, or careful manual tuning, limiting their scalability and applicability across diverse languages and domains. Self-supervised learning has emerged as a more general and scalable solution to the challenges inherent in low-resource NLP. By designing learning objectives that generate supervisory signals directly from raw text, self-supervised methods enable models to learn meaningful representations without the need for human annotation. These representations capture both syntactic structure and semantic relationships, allowing models to develop a deeper understanding of language patterns through exposure to large volumes of unlabeled data. This approach reduces reliance on curated datasets and minimizes the need for language-specific feature engineering.

The motivation for adopting self-supervised learning lies in its ability to achieve competitive performance with significantly reduced dependence on annotated data. This paradigm is particularly beneficial for underrepresented languages, regional dialects, and specialized domain corpora, where labeled resources are scarce, costly, or entirely unavailable. By enabling effective learning from unlabeled text, self-supervised learning supports the development of inclusive, scalable, and adaptable NLP systems, contributing to broader linguistic coverage and more equitable access to language technologies.3. Fundamentals of Self-Supervised LearningSelf-supervised learning is a subset of unsupervised learning in which models are trained using automatically generated labels derived from the data itself. In NLP, self-supervised objectives are designed to capture linguistic structure by predicting missing or transformed elements of text. Common self-supervised objectives include masked language modeling, where a model predicts masked tokens based on surrounding context, and next-sentence prediction, which encourages understanding of sentence-level coherence. Contrastive learning objectives further enhance representation quality by distinguishing between similar and dissimilar text segments.

These training strategies enable models to learn contextual word representations that encode both local and global linguistic patterns. The resulting pretrained models can be fine-tuned on downstream tasks with minimal labeled data, making them particularly suitable for low-resource scenarios.

4. Self-Supervised Pretraining for Low-Resource Languages

In low-resource NLP, self-supervised pretraining plays a crucial role in bridging the data gap. By training models on large volumes of unlabeled text collected from web sources, digital archives, or community-generated content, it is possible to capture language-specific characteristics without manual annotation. Multilingual pretraining has proven especially effective, as it allows knowledge transfer across languages. Shared representations learned from high-resource languages can benefit structurally or lexically related low-resource languages. Techniques such as cross-lingual masked language modeling enable models to align representations across languages, facilitating transfer learning. Domain-adaptive pretraining further enhances performance by exposing models to domain-specific text, allowing them to learn specialized vocabulary and usage patterns relevant to target applications.

5. Downstream Tasks and Adaptation Strategies

Once models have been pretrained using self-supervised learning objectives, they can be effectively adapted to a wide range of downstream NLP tasks even when only limited labeled data is available. The most common adaptation approach is fine-tuning, in which the pretrained model parameters are further optimized using task-specific annotated datasets. Due to the rich linguistic representations learned during pretraining, fine-tuning typically requires only a small number of labeled examples to achieve strong performance, making it particularly well suited for low-resource settings. Self-supervised pretrained models have demonstrated notable improvements across a variety of downstream NLP tasks. These include text classification, where models learn to categorize documents or sentences; sentiment analysis, which involves identifying subjective opinions or emotional tone; part-of-speech tagging, a fundamental task for syntactic analysis; named entity recognition, which focuses on identifying and classifying entities such as names, locations, and organizations; and information extraction, which aims to derive structured information from unstructured text. In many low-resource scenarios, pretrained models significantly outperform models trained from scratch by leveraging previously learned syntactic and semantic knowledge.

Beyond conventional fine-tuning, several alternative adaptation strategies have been developed to further reduce labeled data requirements and computational costs. Parameter-efficient fine-tuning techniques, such as adapter modules, low-rank updates, and selective layer training, allow only a small subset of model parameters to be updated while keeping the majority of the pretrained model fixed. This approach reduces memory usage and training time, making it suitable for deployment in resource-constrained environments. Prompt-based learning represents another promising adaptation strategy, particularly for transformer-based models. By reformulating downstream tasks as masked language modeling or text completion problems, prompt-based methods enable models to leverage their pretrained knowledge with minimal or no additional parameter updates. Similarly, feature extraction approaches utilize pretrained models as fixed encoders to generate contextual embeddings, which are then fed into lightweight classifiers trained on limited labeled data. Collectively, these adaptation strategies enhance the practicality of self-supervised learning for low-resource NLP by minimizing annotation costs, reducing computational demands, and maintaining competitive performance. Their flexibility and efficiency make them particularly valuable for real-world applications in environments with limited data and infrastructure.

6. Evaluation and Performance Considerations

Evaluating natural language processing models in low-resource settings presents a distinct set of methodological challenges that differ significantly from those encountered in high-resource scenarios. One of the primary difficulties arises from the limited availability of labeled test data, which can result in unreliable performance estimates and increased susceptibility to evaluation bias. Small test sets may fail to capture the linguistic diversity of the target language or domain, leading to overoptimistic or inconsistent assessment of model performance.

To address these limitations, researchers commonly employ alternative evaluation strategies such as cross-validation, which allows for more robust performance estimation by repeatedly training and testing models on different data splits. Data augmentation techniques, including paraphrasing, back-translation, and synthetic data generation, are also used to enrich training and evaluation datasets, helping to reduce overfitting and improve generalization. Additionally, transfer evaluation across tasks or domains is often conducted to assess the extent to which learned representations can be effectively reused in related applications, providing insight into model robustness beyond a single task. Empirical evidence across a wide range of low-resource NLP studies consistently demonstrates that self-supervised learning significantly enhances model robustness, generalization capability, and data efficiency. Models pretrained on large volumes of unlabeled text are better equipped to handle linguistic variability and unseen vocabulary, even

when fine-tuned on minimal labeled data. These benefits are particularly evident in extreme low-resource conditions, where only a handful of annotated examples are available.
The pronounced performance gains observed in such settings highlight the effectiveness of representation learning from unlabeled text. By capturing underlying syntactic structures and semantic relationships during pretraining, self-supervised models provide a strong initialization that enables faster convergence and improved performance during downstream adaptation. As a result, self-supervised learning has become a foundational approach for developing reliable and scalable NLP systems in data-scarce environments.
However, evaluation must also consider fairness and linguistic diversity, ensuring that improvements do not disproportionately benefit certain language varieties at the expense of others.

7. Challenges and Limitations

Despite its significant advantages, the application of self-supervised learning (SSL) to low-resource natural language processing presents several persistent challenges that must be addressed to ensure equitable and effective model performance. One of the primary limitations lies in the uneven quality and availability of unlabeled textual data across languages. While high-resource languages benefit from extensive and diverse digital corpora, many low-resource and indigenous languages suffer from sparse, noisy, or domain-restricted text sources. This imbalance can lead to weaker linguistic representations, limiting the generalization capability of self-supervised models and reducing their effectiveness in downstream tasks. Another critical concern is the amplification of bias inherent in unlabeled corpora. Since self-supervised models learn directly from raw text, they may inadvertently internalize and reinforce existing social, cultural, and linguistic biases present in the data. Such biases can manifest in harmful or discriminatory outputs, raising ethical concerns related to fairness, inclusivity, and responsible AI deployment. Addressing these issues requires proactive bias detection, balanced data sampling strategies, and the integration of ethical evaluation frameworks during both pretraining and fine-tuning stages. The computational demands of large-scale self-supervised pretraining pose an additional barrier, particularly for academic institutions, independent researchers, and communities with limited access to high-performance computing infrastructure. Training state-of-the-art models often requires substantial computational power, memory, and energy consumption, which can restrict participation and innovation in low-resource settings. Consequently, there is a growing need for efficient training techniques such as parameter-efficient architectures, model compression, knowledge distillation, and lightweight pretraining approaches that reduce resource requirements without compromising performance. Furthermore, self-supervised models may struggle to adequately capture the linguistic characteristics of languages with complex morphology, rich inflectional systems, or flexible word order.

Languages with limited digital presence or predominantly oral traditions face additional challenges, as insufficient textual data hampers effective representation learning. In such cases, standard pretraining objectives may fail to capture subtle grammatical and semantic nuances, resulting in suboptimal model behavior.

Addressing these challenges requires a multifaceted approach that combines careful dataset curation, innovative model and training strategies, and community-driven initiatives. Collaborative efforts involving linguists, native speakers, and local institutions are essential for expanding high-quality digital resources and ensuring culturally sensitive data collection. By integrating efficient learning methods with inclusive data practices, self-supervised learning can evolve into a more accessible and ethically responsible paradigm for advancing low-resource NLP.

8. Applications and Societal Impact

Self-supervised learning plays a crucial role in enabling the development of natural language processing (NLP) applications for languages and communities that have historically been underserved by mainstream technological advancements. Many of these languages lack large, annotated datasets due to limited digitization, insufficient linguistic resources, or socio-economic constraints. By leveraging vast amounts of unlabeled text, self-supervised learning overcomes these barriers, allowing NLP models to learn meaningful linguistic patterns directly from raw data. This capability facilitates the creation of core language technologies such as machine translation, speech-to-text and text-to-speech systems, information retrieval platforms, and conversational agents that are tailored to local and regional languages. The impact of self-supervised learning extends across critical societal domains, including healthcare, education, and governance. In healthcare, low-resource NLP systems can assist in translating medical information, enabling patient–doctor communication in native languages, and improving the accessibility of health advisories and clinical documentation. In educational settings, multilingual NLP tools can support personalized learning, automated content translation, and intelligent tutoring systems, thereby reduce language barriers and promote inclusive education. Similarly, in governance and public administration, self-supervised NLP applications can facilitate multilingual access to government policies, legal documents, and public service portals, ensuring broader citizen participation and transparency.

Furthermore, the deployment of self-supervised models supports cross-lingual transfer learning, where knowledge learned from high-resource languages can be adapted to structurally or culturally related low-resource languages. This approach not only accelerates system development but also helps preserve linguistic diversity by enabling digital representation for endangered and minority languages. As a result, communities that were previously excluded from digital ecosystems gain greater access to information, communication, and technology-driven services. Overall, the adoption of self-supervised learning contributes significantly to digital inclusion and linguistic equity. By reducing dependency on expensive annotated datasets and promoting scalable multilingual solutions, self-supervised NLP empowers diverse linguistic communities and supports equitable access to technology. As research continues to advance, these methods are expected to play an increasingly important role in bridging the global digital divide and fostering socially responsible AI systems.

9. Future Research Directions

Future research in self-supervised learning for low-resource NLP should focus on reducing computational costs, improving cross-lingual transfer, and developing evaluation benchmarks for underrepresented languages. Techniques such as lightweight models, federated learning, and community-based data collection offer promising avenues.

The integration of linguistic knowledge with data-driven approaches may further enhance performance in low-resource settings. Additionally, ethical considerations such as bias mitigation and data sovereignty should remain central to future developments.

Conclusion:

Self-supervised learning (SSL) has emerged as a transformative paradigm in addressing the longstanding challenges associated with low-resource natural language processing (NLP). Traditional supervised NLP systems rely heavily on large volumes of annotated data, which are costly, time-consuming, and often infeasible to obtain for many languages, dialects, and specialized domains. In contrast, self-supervised learning leverages the inherent structure and statistical patterns of vast amounts of unlabeled text to automatically generate training signals, enabling models to learn meaningful linguistic representations without explicit human annotation. At the core of self-supervised NLP approaches are pretext tasks such as masked language modeling, next-sentence prediction, contrastive learning, and span corruption. These tasks encourage models to capture syntactic, semantic, and contextual relationships within language data. By learning from raw text alone, SSL models develop robust embeddings that generalize effectively across downstream tasks, including text classification, machine translation, named entity recognition, question answering, and sentiment analysis. This capability is particularly beneficial in low-resource settings, where labeled datasets are scarce or nonexistent.

Self-supervised pretraining has been shown to significantly enhance performance when combined with minimal supervision during fine-tuning. Models pretrained on large multilingual or domain-specific corpora can be adapted efficiently to new tasks with only a small number of labeled examples, a property often referred to as few-shot or zero-shot learning. This adaptability enables the rapid deployment of NLP systems for underrepresented languages and emerging domains such as healthcare, legal analysis, and scientific literature mining, where annotated data is both sensitive and limited. Despite its advantages, self-supervised learning is not without challenges. The quality and diversity of unlabeled data play a critical role in determining model effectiveness, as noisy or biased corpora can lead to the amplification of linguistic, cultural, or societal biases. Additionally, the computational requirements for training large self-supervised models are substantial, often necessitating specialized hardware and energy-intensive resources. These constraints raise concerns regarding accessibility, sustainability, and environmental impact, particularly for researchers and institutions with limited infrastructure.

Ethical considerations also remain central to the continued advancement of self-supervised NLP. Since models learn from uncurated text sources, they may inadvertently absorb harmful stereotypes, misinformation, or privacy-sensitive content. Addressing these issues requires the development of responsible data curation practices, bias mitigation techniques, and transparent evaluation frameworks to ensure fairness and accountability in deployed systems. Looking ahead, ongoing research in efficient model architectures, lightweight pretraining strategies, and curriculum-based learning is expected to further enhance the scalability and practicality of self-supervised learning. Innovations such as parameter-efficient fine-tuning, knowledge distillation, and adaptive training objectives promise to reduce computational overhead while maintaining high performance. As these advancements mature, self-supervised learning is poised to play a pivotal role in enabling inclusive, scalable, and effective NLP solutions, empowering languages and domains that have historically remained underrepresented in the digital ecosystem.

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FROM 5G TO 6G:
EMERGING WIRELESS TECHNOLOGIES FOR UBIQUITOUS CONNECTIVITY

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Abstract:
The rapid growth of data-driven services and emerging applications such as immersive extended reality, autonomous systems, industrial automation, and massive Internet of Things is placing unprecedented demands on wireless communication networks. While fifthgeneration (5G) systems introduce flexible architectures and service-oriented designs to support diverse requirements, they face limitations in coverage, energy efficiency, scalability, and global connectivity. This chapter examines the evolution from 5G to sixth-generation (6G) wireless systems with a focus on enabling ubiquitous connectivity. It first reviews essential 5G capabilities and gaps, then presents the vision, performance targets, and service scenarios envisioned for 6G. Core enabling technologies, including new spectrum usage, advanced antenna systems, AI-native networking, and integrated sensing and communication, are discussed in detail. The chapter further explores emerging network architectures and application domains, and highlights key challenges, open issues, and future research directions toward realizing human-centric and sustainable 6G networks.

Keywords: 5G and 6G Wireless Systems, Ubiquitous Connectivity, Terahertz Communication, AI-Native Networks, Reconfigurable Intelligent Surfaces.

Introduction:

Background and Motivation

Wireless communication networks have evolved into a critical societal infrastructure, supporting not only personal communication but also economic growth, industrial productivity, public safety, and social inclusion. Over the past few years, the volume of mobile data traffic has increased exponentially due to high-definition multimedia streaming, cloud-based applications, social networking, and mobile computing. This trend is further intensified by the emergence of new application domains such as immersive extended reality (XR), autonomous vehicles, digital twins, smart cities, and large-scale Internet of Things (IoT) deployments.

Modern applications impose stringent and diverse performance requirements on wireless networks. For example, immersive XR and holographic communication require extremely high data rates and precise synchronization, while industrial automation and remote surgery demand ultra-low latency and near-perfect reliability. At the same time, IoT applications require energy-efficient connectivity for billions of low-cost, low-power devices. Supporting such heterogeneous requirements within a single network infrastructure presents a significant technical challenge.

Wireless generations have evolved to meet prevailing communication needs. 1G supported analog voice, 2G enabled digital voice with basic data, 3G introduced mobile multimedia, and 4G emphasized high-speed packet data. These generations mainly focused on improving data rates and spectral efficiency.

5G marks a shift toward service-oriented design and flexible network architectures that support diverse applications. However, it cannot fully satisfy future digital requirements due to limited high-frequency coverage, rising energy demands, constrained intelligence, and incomplete global reach. These challenges drive the development of 6G, which is envisioned as a platform for truly ubiquitous connectivity, providing seamless communication across devices, environments, applications, and locations.

Objectives and Scope

Fifth-generation (5G) wireless systems represent a major advancement in mobile communication by introducing flexible architectures and service-oriented designs capable of supporting diverse application requirements. Key capabilities of 5G include enhanced mobile broadband for high data rate services, ultra-reliable low-latency communication for missioncritical applications, and massive machine-type communication for large-scale Internet of Things deployments. Technologies such as millimeter-wave communication, massive MIMO, beamforming, network slicing, and edge computing enable improved throughput, reduced latency, and efficient resource utilization. These features position 5G as a versatile platform for modern digital services.

Despite these strengths, 5G faces several limitations. High-frequency operation leads to limited coverage and sensitivity to blockage, while supporting ultra-high reliability at massive scale remains challenging. Energy efficiency, seamless global connectivity, and tight integration with non-terrestrial networks are also constrained. These challenges motivate the vision of sixth-generation (6G) wireless systems. 6G aims to deliver extreme data rates, ultralow latency, near-perfect reliability, and intelligent, context-aware operation. By exploiting new spectrum bands, integrating artificial intelligence, and enabling global three-dimensional connectivity, 6G is envisioned as a foundation for truly ubiquitous, sustainable, and humancentric wireless communication.

5G Overview: Capabilities and Gaps

5G Architecture and Key Services

The 5G system architecture is designed to be modular, flexible, and service-oriented. It consists of two primary components: the Radio Access Network (RAN) and the 5G Core (5GC). The

RAN connects user equipment to the network using advanced radio technologies, while the 5GC provides control and user plane functions through a service-based architecture.

A key innovation in 5G is the separation of control and user plane functions, enabling scalability and flexible deployment. Network functions are virtualized and can be deployed dynamically using cloud technologies. This architecture allows operators to adapt network behavior based on service requirements.

5G defines three major service categories. Enhanced Mobile Broadband (eMBB) focuses on high data rate applications such as ultra-high-definition video streaming and virtual reality. Ultra-Reliable Low-Latency Communication (URLLC) targets mission-critical applications requiring extremely low latency and high reliability, including industrial automation and remote control systems. Massive Machine-Type Communication (mMTC) supports connectivity for a large number of IoT devices with low data rates and energy consumption.

These service types reflect the transition from traditional mobile broadband networks to multi-service platforms capable of supporting heterogeneous applications.

Key 5G Enabling Technologies

Several keys enabling technologies collectively account for the significant performance gains introduced in fifth-generation (5G) wireless networks. One of the most important among these is millimeter-wave (mmWave) communication, which exploits frequency bands well above those used in earlier generations. The availability of wide contiguous bandwidths in the mmWave spectrum enables very high peak data rates, supporting data-intensive applications such as ultra-high-definition video streaming and immersive multimedia services. At the same time, mmWave propagation is characterized by high path loss, limited diffraction, and strong sensitivity to physical obstructions. To overcome these challenges, advanced transmission and reception techniques are required to maintain reliable links.

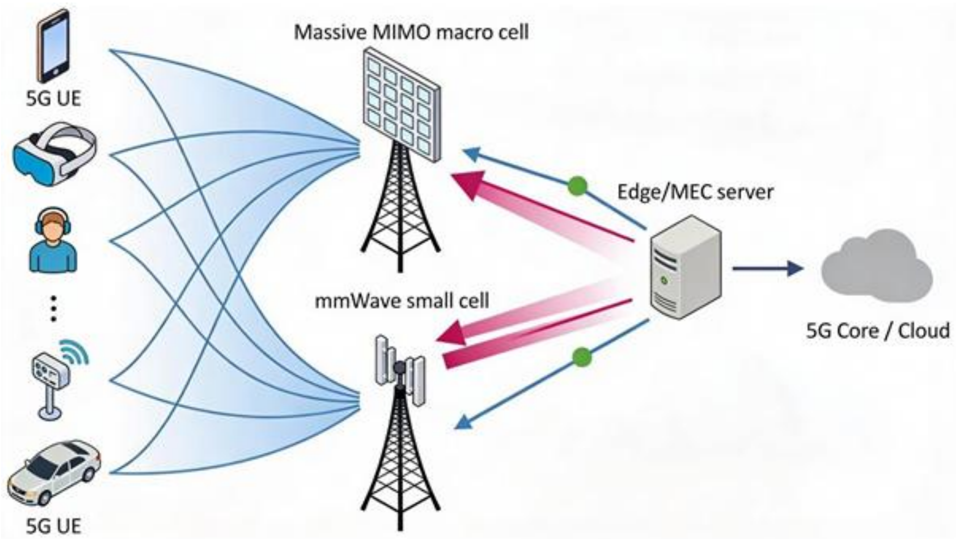

Figure 1: 5G network integrating mmWave access, massive MIMO, and edge computing

Massive multiple-input multiple-output (MIMO) technology plays a crucial role in addressing these propagation limitations. By deploying a large number of antennas at the base station, massive MIMO significantly improves spectral efficiency, link robustness, and spatial reuse. When combined with beamforming, the transmitted energy can be steered toward specific users or devices, thereby extending coverage, enhancing signal quality, and reducing inter-user interference. These capabilities are particularly important for efficient operation in high-frequency bands, where directional transmission is essential.

Another important innovation introduced with 5G is network slicing, which enables service providers to divide a common physical network infrastructure into multiple independent and virtual logical networks. Each of these slices can be individually designed and optimized to satisfy the specific performance needs of different applications or user groups. For instance, one slice may be configured to deliver ultra-reliable and low-latency communication required by industrial automation systems, autonomous vehicles, or critical control operations, while another slice can be optimized to support extremely high data rates for bandwidth-intensive services such as high-definition video streaming, virtual reality, or immersive multimedia applications. This capability allows efficient and flexible utilization of network resources, ensures isolation between services to maintain performance and security, and supports dynamic scaling as traffic demands change.

In addition, edge computing plays a complementary role by deploying computation, storage, and data processing functions closer to end users and devices. This reduces reliance on distant centralized cloud servers, lowers end-to-end latency, and decreases backhaul congestion. As a result, edge computing enables faster response times, supports real-time and mission-critical applications, and significantly improves overall network efficiency and quality of user experience in 5G systems.

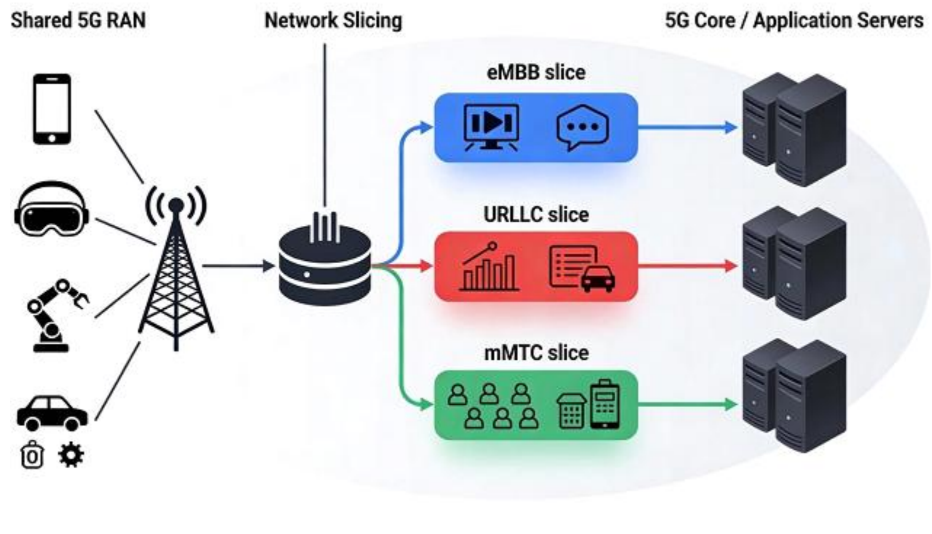

Figure 2: Network slicing supporting eMBB, URLLC, and mMTC services

5G – Advanced Enhancements

Enhanced MIMO and Spectrum Utilization: 5G-Advanced builds on massive MIMO technology by supporting more antenna elements, improved beamforming, and multi-user spatial multiplexing. These enhancements increase spectral efficiency, extend coverage, and improve link reliability. Dynamic spectrum management and advanced carrier aggregation techniques enable better utilization of both sub-6 GHz and mmWave bands, allowing higher throughput and more flexible deployment.

Support for RedCap Devices and Massive IoT: Reduced Capability (RedCap) devices and massive IoT networks are supported through optimized protocols that lower device complexity and power consumption. This allows cost-effective connectivity for wearables, sensors, and industrial devices, facilitating large-scale IoT deployments without compromising network performance or reliability.

XR and Metaverse-Oriented Enhancements: 5G-Advanced introduces features targeting immersive experiences, including ultra-low latency, high data rates, and reliable uplink. These improvements support extended reality (XR), holographic communication, and Metaverse applications, enabling seamless interactive and multi-user virtual experiences.

Limitations Motivating 6G

Although fifth-generation (5G) wireless systems represent a significant step forward in mobile communication, they still exhibit several inherent limitations. One major challenge arises from the use of high-frequency bands, which, while offering large bandwidths, suffer from limited coverage, poor penetration through obstacles, and increased vulnerability to blockage, particularly in dense urban and indoor environments. Ensuring ultra-high reliability and low latency for a massive number of simultaneously connected devices is also difficult, especially as network scale and service diversity increase. Moreover, the densification of network infrastructure and the use of complex signal processing techniques lead to higher energy consumption, raising concerns related to operational cost and sustainability.

Fifth-generation (5G) networks, despite their significant advances, still exhibit notable limitations that constrain their long-term potential. One important drawback lies in their restricted native support for non-terrestrial communication platforms, including satellites, unmanned aerial vehicles, and high-altitude platforms. These airborne and spaceborne systems are vital for achieving seamless global coverage, especially in oceans, rural regions, and disaster-affected areas where terrestrial infrastructure is sparse, damaged, or impractical to deploy. Furthermore, existing security and privacy mechanisms in 5G must be substantially reinforced to handle the increasing complexity, heterogeneity, and openness of modern, software-driven network architectures. As networks incorporate more virtualized functions, edge intelligence, and diverse devices, the risk surface for cyber-attacks, data breaches, and privacy violations grows significantly. Collectively, these challenges highlight the necessity for sixth-generation (6G) systems featuring fundamentally improved coverage, efficiency, reliability, intelligence, and deep integration of terrestrial and non-terrestrial components.

6G Vision, Requirements and Service Scenarios

6G Performance and Design Targets

Sixth-generation (6G) wireless systems are envisioned to achieve performance levels that far exceed those of existing communication technologies. One of the most notable targets is the support of extremely high peak data rates, potentially reaching the terabit-per-second range, which enables seamless transmission of data-intensive content such as holographic media and ultra-high-resolution immersive applications. In addition to peak throughput, 6G aims to significantly enhance the data rates experienced by end users, ensuring consistent and reliable performance across diverse environments. Another critical objective is the drastic reduction of end-to-end latency to sub-millisecond or even microsecond levels, which is essential for real-time interactive services, including remote control, tactile communication, and autonomous systems. Reliability in 6G networks is expected to approach near-perfect levels, supporting mission-critical applications with stringent performance guarantees.

Furthermore, future networks are designed to accommodate extremely high user and device densities, enabling connectivity for millions of devices within a small geographical area. Alongside these ambitious performance goals, energy efficiency and environmental sustainability are treated as fundamental design principles, with an emphasis on low-power operation, intelligent resource management, and reduced carbon footprint.

Service Scenarios

6G wireless systems are designed to support a broad spectrum of advanced service scenarios that extend well beyond the capabilities of earlier networks. Immersive applications, including extended reality and holographic communication, require extremely high data rates, ultra-low latency, and precise timing to deliver seamless user experiences. Tactile internet services further expand these capabilities by enabling real-time haptic feedback, which is essential for remote operation, telemanipulation, and interactive control in critical environments. In parallel, large-scale Internet of Things deployments supported by 6G enable continuous monitoring and intelligent control in areas such as environmental sensing, smart agriculture, and industrial automation. A defining feature of 6G is its support for three-dimensional connectivity, which integrates terrestrial infrastructure with aerial, maritime, and space-based communication platforms. This holistic approach enables reliable and continuous global coverage, ensuring seamless connectivity across diverse geographic regions and application contexts.

Table 1: Performance metrics of 4G, 5G, and envisioned 6G systems

Performance Aspect	4G (LTE)	5G	Envisioned 6G
Maximum achievable data rate	Downlink speeds typically limited to around 100 Mb/s under ideal conditions.	Peak downlink throughput in the range of 10–20 Gb/s, mainly in mmWave deployments.	Expected to support extremely high peak rates, potentially reaching the order of terabits per second.
User-experienced throughput	Practical data rates generally in the range of a few tens of megabits per second.	Typical user rates from several hundred megabits per second up to nearly 1 Gb/s in well-covered areas.	Multi-gigabit per second user data rates anticipated to support immersive and holographic applications.
End-to-end latency	Latency commonly observed in the range of 30–50 ms.	Designed to achieve latency between 1 and 10 ms, with about 1 ms for ultrareliable low-latency services.	arget latency reduced to sub-millisecond levels, with airinterface delays possibly as low as 100 microseconds.
Supported device density	Approximately a few thousand devices per square kilometer.	Designed to connect up to about one million devices per square kilometer for massive IoT scenarios.	Projected to handle ultra-dense deployments with up to several tens of millions of devices per square kilometer.
Frequency bands of	Primarily operates	Utilizes both sub-6	Expected to extend
operation	below 6 GHz, including bands such as 700 MHz to 2.6 GHz.	GHz bands and millimeter-wave frequencies roughly between 24 and 100 GHz.	operation into much higher frequencies, including subterahertz and terahertz ranges.
Primary system objectives	Focused mainly on mobile broadband access and IP-based data communication.	Supports a wide range of services, including enhanced broadband, ultrareliable low-latency communication, massive machine connectivity, and network slicing.	Aims to enable extreme data rates, AI-driven networking, and seamless integration of communication and sensing for ubiquitous connectivity.

Ubiquitous Connectivity Perspective

Ubiquitous connectivity in 6G systems is achieved through a network-of-networks paradigm that seamlessly interconnects multiple access technologies and communication platforms. Rather than relying on a single network layer, 6G integrates diverse terrestrial and non-terrestrial networks to provide continuous and reliable connectivity. Communication becomes user-focused and context-aware, allowing the network to dynamically adapt to varying application requirements, device characteristics, and surrounding conditions. Embedded intelligence distributed across the network enables autonomous decision-making, predictive resource allocation, and proactive optimization of network performance. As a result, 6G systems can deliver seamless connectivity with improved efficiency, reliability, and responsiveness across a wide range of usage scenarios and environments.

Core Enabling Technologies for 6G

New Spectrum and Radio Technologies

4.1.1 THz and Sub-THz Bands

Sixth-generation wireless systems investigate the use of sub-terahertz and terahertz frequency bands to access vastly larger bandwidths than those available in current networks. The availability of such wide spectrum resources makes it possible to achieve extremely high data transmission rates, supporting future data-intensive applications. However, signal propagation at these frequencies is severely affected by high path loss, limited penetration, and sensitivity to environmental factors, which restrict communication range. In addition, the development of efficient radio-frequency components and transceivers at these bands presents significant hardware design challenges. To overcome these issues, advanced waveform design, robust channel coding techniques, and highly directional beamforming methods are essential for reliable and efficient communication in the terahertz spectrum.

4.1.2 Multi-Band Operation

Future wireless networks are expected to support simultaneous operation across multiple frequency bands, ranging from conventional sub-6 GHz spectrum to millimeterwave and higher frequency ranges. By intelligently selecting and combining these bands, the network can adapt to changing channel conditions, user mobility, and service requirements. Dynamic spectrum management allows efficient utilization of available resources, improves link reliability, and ensures seamless connectivity even under fluctuating environmental and traffic conditions, thereby enhancing overall network robustness and performance.

Advanced Antennas and Surfaces

4.2.1 Extremely Large-Scale and Cell-Free MIMO

Extremely large-scale multiple-input multiple-output (MIMO) systems extend the conventional concept of antenna arrays by distributing a very large number of antennas across a wide geographic area. This distributed deployment improves signal coverage, enhances link reliability, and provides more uniform service quality for users, regardless of their location. Building on this idea, cell-free network architectures remove the notion of fixed cell boundaries and allow users to be served cooperatively by multiple access points. By avoiding abrupt handovers and reducing inter-cell interference, cell-free systems significantly improve spectral efficiency, user experience, and overall network performance, making them well suited for future high-density wireless environments.

4.2.2 Reconfigurable Intelligent Surfaces

Reconfigurable intelligent surfaces are engineered structures that can control and modify the behavior of electromagnetic waves in a programmable manner. By intelligently reflecting or redirecting signals, they help improve propagation conditions, extend network coverage, and mitigate interference in challenging environments. Since these surfaces operate with low power consumption and can be deployed on existing structures, they provide a costeffective and flexible solution for enhancing the overall performance of future wireless networks.

AI-Native Networks and Semantic Communication

4.3.1 AI for Network Management

Artificial intelligence plays a central role in future wireless networks by enabling intelligent and predictive management of network resources. Through data-driven learning, AI techniques can anticipate traffic demand, optimize resource allocation, and manage user mobility more efficiently. In addition, AI-based monitoring helps identify faults and performance degradations at an early stage. By embedding intelligence directly into network operations, AI-native networks can autonomously adapt to dynamic conditions, improving reliability, efficiency, and overall service quality.

4.3.2 Semantic Communication

Semantic communication shifts the focus of data transmission from sending exact bit sequences to conveying the underlying meaning of information. Instead of delivering all raw data, the system identifies and transmits only the most relevant content needed for successful interpretation at the receiver. By eliminating unnecessary or repetitive information, semantic communication significantly reduces bandwidth usage and transmission overhead. This approach enhances communication efficiency, lowers latency, and improves reliability, especially in resource-constrained and highly dynamic wireless network environments.

Integrated Sensing and Communication

6G wireless systems are envisioned to tightly integrate sensing and communication functionalities within a unified network framework. Instead of treating these capabilities as separate systems, 6G enables the use of common radio signals and infrastructure for both data transmission and environmental sensing. This integration allows the network to detect, localize, and track objects or events while simultaneously supporting communication services. Such capabilities are particularly valuable for applications like autonomous driving, where real-time awareness of surrounding vehicles and obstacles is critical, as well as for industrial monitoring that require precise observation of machines and processes. Additionally, integrated sensing and communication supports large-scale environmental sensing applications, including weather monitoring and pollution detection. By sharing hardware, spectrum, and processing resources, this approach improves efficiency, reduces deployment costs, and enhances situational awareness across diverse application domains.

Network Architecture and Applications for Ubiquitous Connectivity

Network Architecture for 6G

5.1.1 3D and Non-Terrestrial Integration

6G networks aim to achieve seamless global connectivity by tightly integrating terrestrial communication systems with non-terrestrial platforms such as satellites, unmanned aerial vehicles, and high-altitude platform stations. This multi-layered architecture extends network coverage to remote, rural, and disaster-affected areas where ground infrastructure is limited or unavailable. Aerial and space-based components enhance network resilience by providing backup connectivity during emergencies and supporting dynamic traffic demands. By combining different network layers, 6G enables continuous and reliable communication across land, sea, and air, ensuring robust service availability under diverse environmental and operational conditions.

5.1.2 Cloud-Native and Disaggregated RAN

Cloud-native network architectures leverage virtualization and open interfaces to support flexible and scalable deployment of network functions. By decoupling software from hardware, they encourage innovation, simplify upgrades, and enable faster introduction of new services while improving interoperability across different network components.

Security, Privacy and Trust in 6G

The evolution from 5G to 6G introduces new security and privacy challenges due to increased network complexity, heterogeneous infrastructure, and integration of AI and edge computing.

5.2.1 Threat Landscape in 5G and 6G

Vulnerabilities in Cloudified and Open RAN: Virtualized and cloud-based network functions, along with open interfaces in Open RAN, increase the attack surface, making networks susceptible to misconfigurations, software exploits, and insider threats.

Attacks on Control, Data, and Management Planes: Sophisticated attacks targeting signaling protocols, data flows, and management operations can compromise confidentiality, integrity, and availability, affecting user experience and service reliability.

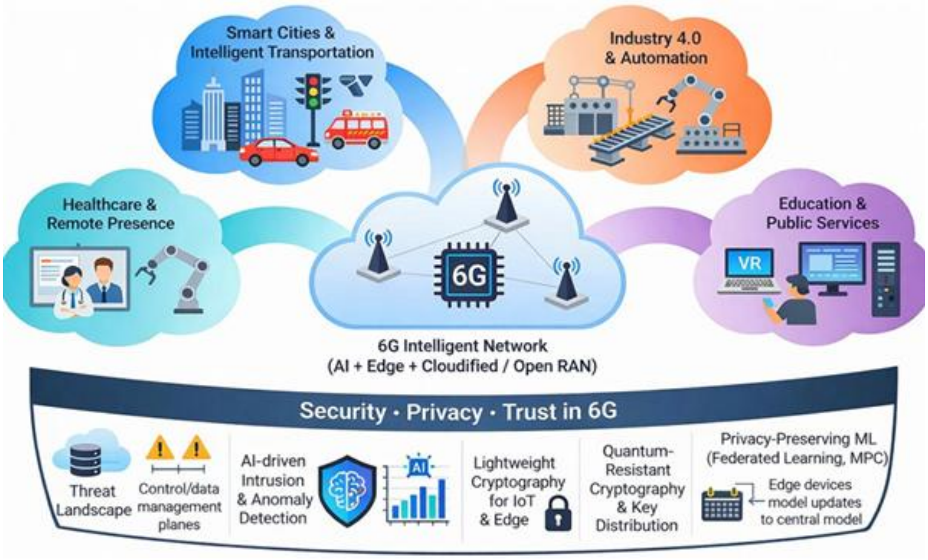

Figure 3: 6G Intelligent Networks: Applications, Security, Privacy, and Trust

5.2.2 Security Enablers and Mechanisms

- AI-Driven Intrusion and Anomaly Detection: Artificial intelligence and machine learning can detect abnormal traffic patterns, identify potential intrusions, and enable automated mitigation, enhancing proactive security across dynamic 6G environments.
- Lightweight Cryptography for IoT and Edge Devices: Energy- and resource-efficient cryptographic solutions are essential for securing massive IoT and edge devices while maintaining low-latency communication and minimal computational overhead.

5.2.3 Emerging Paradigms

- Quantum-Resistant Cryptography and Key Distribution: With the advent of quantum computing, developing quantum-safe encryption and key distribution methods is critical to protect sensitive information.
- Privacy-Preserving Machine Learning: Techniques like federated learning and secure multi-party computation ensure that network intelligence can be extracted without exposing individual user data, balancing analytics and privacy in future networks.

Key Application Domains

5.3.1. Smart Cities and Intelligent Transportation

Advanced wireless technologies enable real-time traffic monitoring, adaptive traffic signal control, smart parking, and accident detection. They also support public safety services such as emergency response coordination, video surveillance, and disaster management, improving urban efficiency and safety.

5.3.2. Industry 4.0 and Automation

Next-generation networks support industrial automation by enabling reliable machineto-machine communication, real-time process control, predictive maintenance, and collaborative robotics. These capabilities enhance productivity, flexibility, and operational efficiency in smart factories.

5.3.3. Healthcare and Remote Presence

High-capacity and low-latency connectivity facilitates telemedicine, remote diagnostics, robotic-assisted procedures, and continuous patient monitoring. Immersive technologies such as extended reality enable advanced medical training and remote consultation.

5.3.4. Education and Public Services

Wireless technologies support interactive and immersive e-learning platforms, remote classrooms, and digital laboratories. They also improve access to public services through online governance, virtual citizen engagement, and inclusive digital service delivery.

Challenges, Open Issues and Future Directions

Technical and Implementation Challenges

Several critical challenges must be addressed to realize the full potential of future wireless networks. One major issue is the development of reliable and cost-effective hardware capable of operating at sub-terahertz and terahertz frequencies, where signal generation, amplification, and detection remain technically demanding. Accurate channel modeling at these high frequencies is also essential, as propagation characteristics differ significantly from those of lower bands and are strongly influenced by environmental factors. In addition, improving energy efficiency is crucial, particularly as network density and computational complexity increase. Ensuring interoperability across diverse technologies, frequency bands, and network architectures is another key challenge, requiring standardized interfaces and coordinated system design to enable seamless integration and operation.

Regulatory and Societal Aspects

Regulatory and societal factors play a crucial role in the evolution of future wireless systems. Effective spectrum regulation is required to ensure fair access and efficient utilization of limited frequency resources across regions and services. Deployment and operational costs must be carefully managed to enable widespread adoption. In addition, sustainability concerns demand energy-efficient and environmentally responsible network designs. Addressing the digital divide is equally important to ensure inclusive connectivity for underserved and remote communities.

Open Research Directions

Future research in wireless communication is expected to focus on several promising directions. The development of new waveforms and advanced coding schemes aims to improve spectral efficiency, robustness, and flexibility under diverse channel conditions. AInative protocol design will enable intelligent, adaptive networking through data-driven decision-making and self-optimization. Green communication techniques are essential to reduce energy consumption and environmental impact. In parallel, human-centric networking emphasizes quality of experience, trust, and sustainability, ensuring that future networks effectively serve societal needs.

Conclusion:

This chapter has provided a comprehensive discussion on the progression from fifthgeneration to sixth-generation wireless communication systems, emphasizing the technological advancements and architectural innovations that support the vision of ubiquitous connectivity. While 5G establishes a flexible and service-oriented foundation capable of supporting diverse applications, 6G significantly extends this framework by incorporating new spectrum resources, advanced radio technologies, artificial intelligence– driven networking, and seamless integration of terrestrial and non-terrestrial platforms. These enhancements enable unprecedented levels of performance, intelligence, and coverage. By delivering seamless, context-aware, and energy-efficient communication services across diverse environments, 6G is poised to play a transformative role in shaping future digital societies, supporting emerging applications, and fostering inclusive, sustainable global connectivity.

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SCIENCE AND TECHNOLOGY INNOVATIONS FOR SUSTAINABLE SOLUTIONS

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Abstract:
Innovative Approaches in science and Technology Research presents forward-looking developments across multiple scientific and technological fields, with a strong focus on cross-disciplinary collaboration and impactful applications. The collection showcases leading research in areas including artificial intelligence, sustainable energy systems, biotechnology, and advanced materials, illustrating how inventive methods and technologies are being applied to solve pressing global problems. It emphasizes the use of emerging tools, original experimental strategies, and computational techniques to speed up scientific discovery and technological progress. By bringing together insights from researchers, industry professionals, and policymakers, this volume delivers a broad perspective on state-of-the-art research, encouraging collaboration and shaping future directions in science and technology.
Keywords: Interdisciplinary Research, Scientific Innovation, Technological Advancement, Emerging Technologies, Artificial Intelligence, Sustainable Energy, Biotechnology, Advanced Materials, Computational Methods, Global Challenges.

Introduction:

Science, technology, and innovation are key drivers in achieving the Sustainable Development Goals. They help boost productivity, transform economies, accelerate growth, create quality employment, and reduce dependence on fossil fuels. Additionally, they play a crucial role in developing life-saving medicines, improving healthcare systems, promoting food security through sustainable farming, enhancing agricultural yields, reducing the physical burden of domestic work, and making reproductive health safer. Strengthening a country's capacity in science, technology, and innovation and applying these effectively in economic and social activities is essential for expanding human capabilities and advancing sustainable development. Moreover, these tools are central to both national and global efforts to address the interconnected economic, social, and environmental challenges of development. However, while science and technology are critical to tackling today do sustainability crises, their impact must be understood within broader cultural and historical contexts. Although the world faces shared challenges, the experiences and capacities of different countries, and even regions within countries, vary significantly.

Innovation extends beyond creating new devices; it also encompasses social and organizational changes, such as new business processes or adaptive management practices. Many innovations involve both technological advances and shifts in social practices. The information technology revolution of the past two decades illustrates this combination: e-mail, messaging apps, and voice-over-Internet tools like Skype and WhatsApp have replaced letters and faxes, increasing the frequency, speed, and affordability of communication. During the COVID-19 pandemic, platforms like Zoom, MS Teams, and Webex enabled not only small meetings but also large international conferences to take place online, reducing the need for travel.

Innovation is closely linked to the idea of creative destruction, in which new technologies or products replace older ones. While this drives economic progress, it also creates social disruption: individuals and groups reliant on outdated technologies may lose opportunities, while those adopting new technologies gain advantages. This dynamic explains why some social groups resist technological change, as historically seen with British typesetters opposing automation.

In summary, innovation involves both technological and social transformation. Its full potential is realized when countries cultivate inclusive knowledge systems and innovation strategies that respond to societal needs, respect cultural contexts, and advance sustainable development goals.

Interdisciplinary Research:

This section discusses the processes that constitute IDR, and the outputs of research that could be tapped to measure IDR. The process of integration – whether cognitive or social is more difficult to observe (and measure) than are the results of the process, which are largely found in published literature. This may explain why more literature has focused on the outputs of research rather than the processes. Measurement of scientific output for the purposes of creating indicators is traditionally done using bibliometric approaches, so a large part of this review focused on bibliometrics. Bibliometrics have been refined over four decades based on the widely-held view that the scientific research process is incomplete without publication. Price (1978) argued that publication provides the function within science of correction, evaluation, and acceptance by a community. (1)

Education for Knowledge Society:

Learning and Scientific Innovation Environment:

The knowledge society represents a rapidly evolving socio-economic structure within contemporary civilization. As a component of modern society, it aims to employ scientific reasoning as the main driver of economic growth and social progress. In this context, science increasingly becomes the primary generator of new knowledge, while knowledge itself takes on the role of a fundamental organizing principle of society.

Education is central to developing young individuals with strong capacities for scientific creativity; therefore, research-oriented education serves as a cultural and intellectual foundation of the knowledge society. This form of education relies on pedagogical approaches that reflect the methods and logic of scientific inquiry. It is characterized by significant institutional diversity, including research-focused schools and universities, as well as entrepreneurial universities. These institutions are linked through continuity in scientific cognition, learning environments, and instructional practices.

The structural foundation of research education is formed through cluster-based and networked partnerships involving research institutes, high-technology enterprises, and innovation-support organizations. Establishing dynamic, research-driven learning environments centered in schools and universities is essential for preparing young people to actively contribute to the creation of knowledge. Addressing this issue at the theoretical level enables the identification of key features required of educational institutions operating within the framework of a knowledge-based society. (2)

Recent Advancements in Emerging Technologies for Healthcare Management Systems

The advancement of information technology (IT) has resulted in significant improvements in health care services, particularly in remote health monitoring. One of the primary purposes of employing physical sensor networks is to focus on disease prevention and early identification of high-risk disease disabilities. Today, smart technologies and sophisticated instruments (such as smart wireless and wearable sensors) have substantially risen for rapid monitoring and control of patients' situations via prompt access and continuous assessment of patients' vital health signs .

The capacity of such smart devices to store and transport data is critical in several forms of healthcare or medical care (for example, telemedicine). Wearable sensors are primarily used to observe and track patients' health problems and status, and a variety of other health-related functionalities. Smart devices, specifically wearable sensors, have attracted a lot of attention in the last decade, mostly in the healthcare field. Such devices seek to derive therapeutically important health-related data from physical (body) indicators such as heart rate (HR), blood pressure (BP), body temperature, respiration rate, and body motion. That is, basic health information is derived and shared using applicable wearable sensors and wearable sensor networks. Wearable sensor networks (WSNs) are made up of a variety of health-related sensors. Such networks' sensors are put on various regions of the body, and these sensors may be worn or implanted on the patient's body. Each of these sensors has unique criteria for identifying and recording symptoms (health-related data). However, due to many diseases and impairments, patient monitoring continuity for prompt medical intervention and delivery is pivotal. As a result, using WSNs to monitor patients is a key area of deployment of smart wearable technology in the healthcare domain.

Furthermore, the successful alliance of AI and healthcare has morphed into improved patient healthcare in areas ranging from hospital productivity and patient safety to quality medical treatment. Credence to patient empowerment and a more equitable dialogue between doctors and patients. A practical example is the use of cloud computing with AI to enhance access to health data and the administration of medical resources. In terms of data, patients' health data are required to tailor specific patient treatment and it can be further utilized for disease prediction and healthcare policymaking through big data analytics (BDA). The IoT as a tool can be paired with AI-based technologies or platforms to further improve and promote quality healthcare delivery. The success of IoT in various application domains serve as indicator for its acceptance and integration with wearable sensors and AI technologies for quality healthcare delivery.

Wearable sensors are used as objects or components in IoT and are controlled via the communication links such as Bluetooth, Wi-Fi and in recent time, the Internet. (3)

Calibrating the Effectiveness of a Question Paper Evaluation Tool Using Automatic Keyword Extraction

Ext pre-processing and information extraction techniques have become increasingly important in the systematic evaluation of student performance within academic settings (Delavari *et al.,* 2008). Assessment methods, particularly examinations, play a vital role in determining the effectiveness of instructional practices and learning outcomes and continue to be an integral component of formal education systems (Liu and Wu, 2009; Garfield *et al.,* 2011; Lemons and Lemons, 2013; Dunham *et al.,* 2015). Examinations are commonly employed to measure students' understanding and assimilation of course content. Furthermore, the results obtained from these assessments provide meaningful insights into learners' cognitive processes, behavioral patterns, and skill development (Jones and Harland, 2009).

Within the undergraduate assessment framework of Goa University, written examinations constitute a major instrument for evaluating academic achievement. The extent to which such examinations effectively assess student capability is largely determined by the quality, relevance, and cognitive level of the questions included in the examination paper (Jones and Harland, 2009). This research undertakes a comparative analysis of examination question papers with respect to the university-prescribed syllabus and Bloom's Taxonomy in order to validate the effectiveness of a Question Paper Evaluation Tool developed for theoretical subjects, including Software Engineering. The remainder of this thesis is organized as follows: a review of related literature, a description of the research methodology, a discussion of the problem statement and experimental results, and a concluding section. (4)

Tracking Emerging Technologies in Energy Research: Toward A Roadmap for Sustainable Energy

Energy is a fundamental pillar of modern society and a critical driver of economic development. In recent decades, sustainable and renewable energy systems have been widely recognized as essential components of a viable long-term energy strategy. Despite this recognition, the current global energy system remains largely unsustainable. In 2001, approximately 80% of global primary energy consumption was derived from fossil fuels, which continue to dominate both the transportation sector and stationary applications such as electricity generation. However, the production of fossil fuels is expected to decline by the middle of this century, raising concerns regarding long-term energy security.

In addition to resource depletion, the combustion of fossil fuels is the primary contributor to anthropogenic greenhouse gas (GHG) emissions, which are widely acknowledged as the main driver of climate change. Consequently, there is an urgent need to improve energy efficiency and to develop alternative energy sources capable of reducing carbon dioxide (CO_2) emissions. These measures must complement existing renewable energy technologies, including hydropower, which currently represents the most mature renewable energy source.

Reducing primary energy consumption derived from fossil fuels and expanding the exploitation of renewable energy resources are among the most important objectives for achieving the climate protection targets established by the Kyoto Protocol in 1997. Although conventional energy sources such as oil, natural gas, and coal continue to satisfy the majority of global energy demand, renewable energy technologies must assume a more prominent role in future energy supply systems and energy conservation strategies. In industrialized countries, the Kyoto Protocol has significantly influenced energy policy development at regional, national, and international levels, accelerating the transition toward more sustainable energy systems.

To achieve the objectives of sustainable energy development, a rapidly expanding body of research and scholarly publications has emerged worldwide. Nevertheless, research priorities and strategic focuses vary considerably among countries. Investment in technological innovation is widely recognized as a fundamental prerequisite for the development of future sustainable energy systems. Consequently, energy research planners are required to maintain a comprehensive perspective on advances across diverse scientific and technological fields and to make strategic decisions regarding the allocation of limited resources to promising and emerging technologies, particularly in situations where overall research budgets are constrained or declining. Within this context, methodological tools such as technological forecasting and technology road mapping have gained increasing importance as decision-support mechanisms. These approaches enable the systematic identification, evaluation, and prioritization of technological options under conditions of uncertainty. In the modern knowledge-driven economy, growth increasingly depends on the effective application of scientific and technological innovations. Consequently, identifying emerging research areas within the vast and rapidly expanding body of academic literature has become a critical challenge for R&D managers and policy makers. Broadly, two approaches are commonly used to achieve comprehensive awareness of global research trends. The first is an expert-based approach, which leverages the tacit knowledge and experience of domain specialists. The second is a computer-based approach, which systematically analyzes explicit sources of information, including newspapers, journals, and scholarly publications.

The expert-based approach, however, is becoming progressively difficult to implement due to the sheer volume of available information. Moreover, individual scientists are often required to focus on a limited number of subfields in order to remain up-to-date, rendering this approach increasingly labor-intensive, time-consuming, and susceptible to subjective bias. These limitations highlight the growing need for complementary, data-driven methods to support strategic research planning. (5)

The Impact of Science and Technology on Society:

Science and technology continue to shape the world around us in ways that are both profound and far-reaching. They influence not only how we live, work, and interact, but also our core values and beliefs. From the ways we eat, dress, and travel to how we experience the quality and length of life, technological and scientific progress has redefined human existence. Even our earliest sedentary societies relied on innovations to address social challenges, shape culture, and improve wellbeing. Yet, this power is double-edged: the same advances that make life easier also give humans the capacity to harm the environment and ourselves.

Since the Industrial Revolution, developments in energy, materials, engineering, medicine, biotechnology, and communications have accelerated at an unprecedented pace. These changes have improved health, prosperity, and overall quality of life for millions. What strikes me most is how deeply human progress is intertwined with our inventions how every leap in technology carries both promise and responsibility. Observing this, I realize that understanding science and technology is not just about tools and machines; it's about understanding ourselves, our societies, and the choices we make for the future.

Effect of Technology Change on Society:

Science and technology shape almost every aspect of modern life, touching people across the globe. Looking at how technology changes or stays the same offers insight into how humanity has evolved. Early inventions like fire and the wheel transformed daily life, and technological progress has unfolded differently across historical eras, from hunting and gathering to agrarian and industrial societies. Advancements in technology have allowed people to live longer, healthier, and more productive lives. They create new ways to communicate, travel, build, learn, heal, and entertain. Even a single invention can ripple through society, influencing culture, education, politics, and social attitudes. For instance, the radio shaped entertainment and knowledge in countless ways, while industrialization relied on innovations that sparked profound societal changes. Today, technology continues to guide the way we live, interact, and adapt, showing that human progress is deeply intertwined with our inventions and discoveries. (6)

Conclusion:

Technology has always been a central force in shaping human societies. From the earliest inventions, like the wheel and irrigation systems, to modern breakthroughs in communication, healthcare, and industry, technological innovations have consistently transformed the way we live, work, and interact with one another. These changes are not merely practical; they influence culture, values, and the way people think about the world. For example, early agricultural tools allowed communities to settle, build infrastructure, and develop governance systems, laying the foundations for civilization itself.

In the modern era, technological advancements have accelerated at an unprecedented pace. Innovations such as the internet, smart phones, renewable energy, and artificial intelligence have altered nearly every aspect of daily life. Healthcare technologies extend life expectancy and improve quality of life, while communication tools make it possible to connect across continents instantly. Industry and manufacturing benefit from automation and precision engineering, increasing efficiency and productivity with these advances come challenges ethical dilemmas, environmental concerns, and social inequalities highlighting the need for responsible and thoughtful use of technology.

Reflecting on this, I realize that technology is not neutral; it shapes and is shaped by human choices. Every invention carries potential for both progress and harm. Radio changed not just entertainment but education, politics, and public opinion. Similarly, the Industrial Revolution revolutionized societies but also introduced environmental degradation and labor struggles. Today, as we develop AI, biotechnology, and space exploration, we face similar questions: How can we ensure that these innovations benefit humanity while minimizing risks?

Ultimately, technology is a mirror of human ambition, creativity, and responsibility. It is a tool for solving problems, improving lives, and connecting people but it is also a reminder that progress comes with choices. Observing how past and present innovations shape societies, I am struck by the interconnectedness of human life and technology. Our future will depend not only on what we invent but also on how wisely we use these inventions to address global challenges, preserve our environment, and foster equitable progress.

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ELECTROMAGNETIC BEHAVIOR OF LEAD FREE FERROELECTRICS AT MICROWAVE FREQUENCIES

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Abstract:
Driven by environmental concerns, lead-free ferroelectrics are sought to replace traditional PZT. This work investigates the microwave properties of [Lead-Free Composition, synthesized via [Synthesis Method]. Characterization at microwave frequencies (e.g., 100 MHz - 3 GHz) reveals a high dielectric constant and significant tunability (upto~60%), attributed to [Microstructure, e.g., fine grain size]. These results highlight the material's potential for tunable microwave devices, offering a greener alternative for next-generation wireless communications.
Keywords: Synthesis, Characterization, Microwave Absorption, Penetration Depth, Microwave Conductivity

1. Introduction:

Today's wireless communications and information systems are heavily based on microwave technology. Current trends indicate that in the future along with microwaves, the millimeter wave and terahertz technologies will be used to meet the growing bandwidth and overall performance requirements. Moreover, motivated by the needs of the society, new industry sectors are gaining ground; such as wireless sensor networks, safety and security systems, automotive, medical, environmental, food monitoring, radio tags etc. Ceramic materials and single crystals showing ferroelectric behavior are being used in many applications in electronics and optics. Each and every material has its own set of electrical characteristics related to its dielectric properties. Materials which can absorb microwaves can eliminate electromagnetic wave pollution. Wide spread applications of electromagnetic absorbers, have inspired engineers to explore about optimal design with available algorithms. Knowing these properties precisely enables scientists and engineers to use the appropriate materials for intended applications, such as the design of ferroelectrics. The dielectric constant is an essential property of dielectric materials hence its determination is very important. The most used technique depends on the measurement of either reflection coefficients or resonant frequencies. In the later case material is used to load a resonant cavity and the sample permittivity is evaluated from the shift of the resonant frequency value, compared to that of the empty cavity.

A large number of applications of ferroelectric ceramics also exploit properties that are an indirect consequence of ferro electricity, such as dielectric, piezoelectric, pyroelectric and electro-optic properties. In 1970, the Bell Telephone Laboratories had published successive thorough investigation soft he optical, electrical, and structural properties of SBN crystals. SBN belongs to the group of relax or ferroelectrics. A typical phenomenon for this class is a broadened phase transition which is probably caused by the wide variation of the non equivalent crystallographic positions in its structure. The high values of the electro- optic and pyroelectric coefficients oriented further work mainly towards holographic data storage, photorefractive devices and pyroelectric applications. Thus, SBN is very good candidate with large number of other applications like semiconductor and in photo optic applications. Microwave absorbing materials have an important application in the military and the civil technology such as the stealth, microwave darkroom and electromagnetic interference protection. The complex permittivity is an important factor which can be altered to achieve maximum absorption of the electromagnetic waves. Permittivity relates to the material's ability to transmit (or permit) an electric field. Permittivity also depends on the physical properties such as density and composition of the material and it change with temperature and frequency.

Another main reason that SBN is found most important due to environmental concerns safety and health view point, that lead free materials are being considered for many applications as mentioned above. The objective of this work is the synthesis of SBN ferroelectric material by low-cost solid-state reaction route at low temperature. In the present case we report the synthesis of SBN ferroelectric material by solid-state reaction synthesis route along with the electromagnetic behavior in the microwave frequency band. To the authors knowledge there are no reports on the microwave properties of SBN ceramics, perturbations by wave guide (absorbance and reflectance) as well as VSWR methods at X and Ku band.

2. Experimental Details

Synthesis:

AR grade chemicals of high purity Lead Free Ferroelectrics materials were used as starting materials. Powder was crushed for homogenization using agate mortar in acetone medium for 1 hour to get the fine powder. This powder was again mixed in stoichiometric proportion and ground for 4 hours in acetone medium to obtain desired stoichiometry in the resultant compounds. This mixture was initially sintered at 1200 ˚C for 10 hrs and further at 850˚C for 48 hours in a muffle furnace.

Characterization:

The single phase formation of the compounds was con- firmed by X-ray diffraction patterns obtained using Cr-K_{α}radiations. The surface morphology was studied using scanning electron microscope. Further the samples were characterized by using IR spectrophotometer to identify and understand the aspect of bonding in the present samples in the range of 400–4000$cm^{-1}$with KBr solvent. The Raman spectra of the samples were recorded in the spectral range of 36–3600 cm^{-1} using Fourier-Transform Raman spectrometer Nd: YA Glaser source with excitation wavelength of 1064 nm and resolution of 4 cm^{-1} at 336 mW laser power. Transmission of microwaves due to SBN ceramics was measured by reflectometer set up consisting of the X and Ku band generator, isolator, attenuator, directional coupler and RF detector.

3. Influencing Factors at Microwave Frequencies:

Microstructure: Smaller, more homogeneous grain sizes achieved through advanced sintering techniques (like microwave sintering) generally improve the dielectric properties and reduce defects.

Doping/Substitution: Strategic doping (e.g., Mn,) is used to lower dielectric loss and enhance tunability and stability over a wide temperature range, improving suitability for practical devices.

Processing Method: Synthesis methods like sol-gel or semi-solution techniques can lead to better microstructures and enhanced performance compared to conventional solid-state reactions.

Domain Wall Dynamics: In the ferroelectric phase, dielectric dispersion at microwave frequencies depends on domain wall vibrations. Single-domain crystals show less dispersion than multi-domain ones.

4. Microwave Absorption:

Microwave absorption in materials depends on two main parameters: impedance matching (allowing waves to enter the material with minimal reflection) and attenuation characteristics (the ability to dissipate the absorbed energy internally).

Impedance Matching: For effective absorption, the material's impedance must be close to that of free space, which means balancing its complex permittivity and permeability.

Attenuation Mechanisms: The absorbed electromagnetic energy is converted into other forms, primarily heat, through specific loss mechanisms.

5. Microwave Absorption Mechanisms in Lead-Free Ferroelectrics

Pure lead-free ferroelectric materials, such as barium titanate, barium niobate, and bismuth sodium titanate (BNT)-based systems, are primarily dielectric loss materials.

- Dielectric Loss (Dielectric Relaxation): This is the dominant mechanism in ferroelectrics. When exposed to an alternating electric field (like a microwave), electric dipoles within the material align with the field. As the field changes, the reorientation of these dipoles dissipates energy as heat.
- Dipolar Relaxation: Significant in the microwave frequency range, where polar molecules align and reorient with the oscillating field.
- Ionic Polarization: Displacement of positive and negative ions within the crystal lattice also contributes to energy loss.

- Interfacial Polarization (Space-Charge Polarization): Occurs at interfaces between different phases (e.g., grain boundaries, defects). This is significant in polycrystalline ceramics and nano composites.
- Conductive Loss (Ohmic Loss): The presence of free charge carriers and defects (like oxygen vacancies in doped can lead to electrical conductivity. Induced currents in the material dissipate energy as heat (ohmic losses). This can be a major factor, especially in materials exhibiting hopping conduction.
- Magnetic Loss: Pure ferroelectrics are generally non-magnetic. Therefore, they exhibit negligible magnetic loss at microwave frequencies.

6. Penetration depth:

Penetration depth in lead-free ferroelectrics at microwave frequencies depends heavily on the material's complex permittivity (dielectric constant and loss tangent), which varies with frequency, temperature, and composition, but generally, high dielectric loss and strong absorption lead to *shorter* penetration depths, meaning microwaves die out faster; while materials with low loss and high density (like certain BZT-BCT or BFN ceramics) can allow deeper penetration, though specific values require experimental measurement

Key Factors Influencing Penetration Depth:

1. Complex Permittivity (€*): Penetration depth (**δ**) is related to the material's properties by (**δ** =1/ **ω** √μ€*).
2. Dielectric Loss (tan δ): Higher loss (more absorption) results in shallower penetration.
3. Frequency: Higher frequencies generally reduce penetration depth.
4. Composition & Structure: Lead-free materials (like BZT-BCT, BFN) have varied properties; doping and sintering methods (microwave vs conventional) alter density and defects (like oxygen vacancies) that affect loss and permittivity.

General Behavior in Lead-Free Ferroelectrics:

- **Frequency Dispersion:** Dielectric constant often drops as frequency rises (dipoles can't keep up), while loss tangent can vary, showing peaks related to domain wall motion or defects.
- **Microwave Sintering:** Can create smaller grains and higher densities, impacting microwave absorption.

Specific Examples:

- Studies on **Strontium Barium Niobates (SBN)** report microwave penetration depths, but specific values vary and are often studied in thick films for microwave circuits.
- Materials like **(0.5)BZT–(0.5) BCT** show high dielectric constants but also potential for use in actuators, indicating interaction with electric fields.

7. Microwave Conductivity:

For lead-free ferroelectrics, microwave conductivity involves charge carriers oscillating between potential barriers, leading to significantly higher AC conductivity (S/cm range) than DC, often revealing polaron conduction and dielectric losses, especially in materials like barium niobates and doped BaTiO3 systems, crucial for their microwave device potential (tunable filters, absorbers). The conductivity varies greatly with composition, frequency (GHz range), temperature, and processing (sintering), with key factors being domain wall contributions and specific material structure.

Key Aspects of Microwave Conductivity:

- **Frequency Dependence:** AC conductivity at GHz frequencies is often much higher (orders of magnitude) than DC conductivity because localized carriers can respond to high-frequency fields.
- **Mechanism:** High-frequency conduction often involves charge carriers (polarons) hopping or oscillating between energy barriers, rather than continuous drift.
- **Material Specifics:**
  - **Barium Niobates (e.g., $SrBaNb_2O_6$):** Show varying microwave conductivity (0.17 - 6.5 S/cm) depending on Sr content, linked to polaron conduction and dielectric loss minima.
  - **Doped $BaTiO_3$ (e.g., $(Ba,Ca)TiO_3(Ba,Zr)TiO_3$):** Microwave sintering improves properties, with compositions exhibiting potential for tunable devices due to controlled dielectric properties.
  - **Strontium Tantalates (e.g., $SrTa_2O_6$):** Show different permittivity/loss depending on phase (β vs. β'), impacting microwave antenna applications.
- **Processing Influence:** Microwave sintering or processing significantly affects microstructures, leading to different conductivity and dielectric responses compared to conventional methods.
- **Applications:** Low microwave loss and high tunability are desired for microwave applications like tunable filters, resonators, and antennas, with these lead-free materials serving as environmentally friendly alternatives.

Conclusion:

The $Sr_xBa_{1-x}Nb_2O_6$ceramic were successfully synthesized by low cost effective, uncomplicated solid state reaction. The XRD reveals tungsten bronze structure of sample, SEM provide a variation in morphology and increaseingraingrowthduetostrontiumconcentration.IR and Raman broad peak in the region 400 to 850 cm^{-1}due normal modes of vibration, dynamics of isolated NbO_6^{7-}anionshavebeenreported. VSWR method perturbation technique has been used for the evaluation of dielectric parameters of dielectric material at microwave frequencies. The analysis of the expressions for dielectric constants and loss factors of SBN ceramics has been reported first time by the author. The VSWR technique was successfully implemented for the calculation of complex permittivity of the SBN ceramics and it is an efficient tool capable of detecting the changes in microwave properties. According literature survey, there are no reports about the complete study of complex permittivity of SBN ceramics, systematically at microwave regions. The dielectric constant lies in the range 3.9 to 23.8. Microwave conductivity decreases withincreaseinstrontiumcontentandintherange0.17 to 6.5 S/cm.

These SBN ceramics can be a good candidate since large dielectric constants are noteworthy because they enable capacitors and microwave components, semiconductor memory; nonvolatile memory; nonvolatile logic to be fabricated, for use in communications, navigation, and various types of radar.

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SUSTAINABLE SYNTHETIC APPROACHES TO PARACETAMOL AND IBUPROFEN: A GREEN CHEMISTRY PERSPECTIVE

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Abstract:

This chapter explores sustainable synthetic strategies for two widely used pharmaceuticals—paracetamol and ibuprofen—through the lens of green chemistry. For paracetamol, three renewable phenol-based synthetic routes reported in the literature are examined: acetamidation of hydroquinone, imination and reduction of benzoquinone, and hydrogenation of 4-nitrophenol. Green Chemistry metrics and industrial feasibility were used to evaluate each route. Among them, the 4-nitrophenol pathway emerged as the most promising, offering high yields, improved conversion efficiency, and favorable environmental performance when compared to traditional industrial methods. In parallel, the synthesis of ibuprofen is reviewed, contrasting the conventional six-step process—which involves hazardous reagents, low atom economy, and substantial waste generation—with a modern three-step green synthesis. The green route demonstrates significant environmental and process advantages, including a higher atom economy, minimized hazardous by-products, and the use of recyclable materials. Together, these case studies underscore the transformative potential of green chemistry in advancing sustainable pharmaceutical manufacturing.

Keywords: Paracetamol, Renewable, Sustainable Synthesis, Ibuprofen, Aspirin, Green Chemistry, NSAIDs

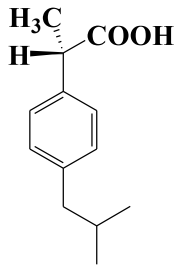
Introduction:

Paracetamol, also known as 4-hydroxyacetanilide, was first synthesized in 1878 by the American chemist Harmon Northrop Morse and introduced into clinical use a few years later by von Mering[1, 2]. Initially, it was overshadowed by phenacetin, which became the analgesic of choice for several decades[3]. However, the significance of paracetamol became more evident in the mid-20th century when Brodie and Axelrod identified it as the active metabolite of both acetanilide and phenacetin, and linked phenylhydroxylamine—a metabolite of acetanilide—to methemoglobinemia[4]. With increasing awareness of phenacetin's toxicity, including risks of nephrotoxicity and psychotropic effects, paracetamol regained prominence and began to replace its predecessor[5, 6].

By the 1980s, paracetamol had become one of the most widely used drugs for treating pain and fever[7]. Its utility extended beyond medicine, finding applications in chemical industries as a stabilizer, intermediate, and even in ecological control[8]. However, its production remains geographically concentrated, leading to supply vulnerabilities, particularly in countries with strict environmental regulations that make manufacturing more costly[9]. This has prompted growing interest in developing greener, more sustainable synthetic routes to ensure broader and more reliable access[10, 11].

Parallel to the rise of paracetamol, another class of drugs—non-steroidal anti-inflammatory drugs (NSAIDs)—was reshaping the field of pain management[12]. The journey began with aspirin, synthesized in 1883 in Germany by chemists at Friedrich Bayer & Co[13], as a more tolerable derivative of salicylic acid, a natural compound known for its analgesic and antipyretic properties[14]. Although salicylic acid caused severe gastric irritation in its native form[15], acetylation of the phenolic hydroxyl group led to aspirin—a major breakthrough that retained therapeutic effects with reduced gastric impact. Nevertheless, aspirin still posed gastrointestinal risks, especially with long-term use.

By the mid-20th century, the medical community began seeking safer alternatives[16]. This effort led to the discovery of ibuprofen in the 1960s by chemists at the Boots Pure Drug Company in Nottingham, England. Ibuprofen, chemically known as (±)-2-(4-isobutylphenyl)propionic acid, offered similar therapeutic benefits to aspirin but with significantly improved gastrointestinal safety. Unlike aspirin, which irreversibly inhibits cyclooxygenase (COX) enzymes, ibuprofen acts through reversible inhibition[17], contributing to its favorable safety profile.



(*S*)-Ibuprofen

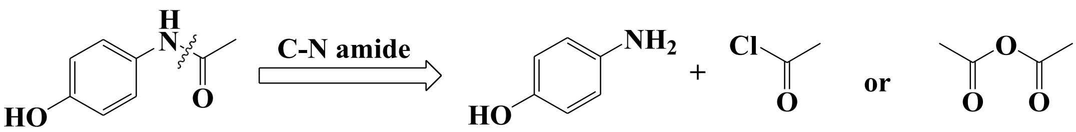
A unique feature of ibuprofen is its chirality. It exists as two enantiomers, but only the (S)-(+)-enantiomer is pharmacologically active[18]. Interestingly, when the racemic mixture is administered, the human body can convert a substantial portion of the inactive (R)-(–)-enantiomer into the active (S)-form through enzymatic chiral inversion[19]. While enantiomerically pure drugs are often preferred for their enhanced potency, lower effective doses, and reduced side effects[20], the racemic mixture of ibuprofen remains widely used due to its effectiveness, lower cost, and proven safety in large populations[22].

Examples of chirality's impact on drug activity abound in medicinal chemistry, reinforcing the importance of stereochemistry in drug design and development[21]. Although the active Senantiomer (dexibuprofen) is marketed in some regions as a potentially more efficient alternative, the clinical advantages over the racemic drug have not been deemed sufficient to replace it widely.

The transition from aspirin to ibuprofen not only signifies a leap in NSAID pharmacology but also highlights the evolution of stereoselective synthesis, metabolic insight, and rational drug development[23]. Alongside paracetamol, these advancements reflect the dynamic nature of pharmaceutical chemistry—balancing efficacy, safety, and accessibility. Today, as environmental and supply chain challenges grow more complex, there is a renewed focus on sustainable synthesis methods. Green chemistry principles are guiding efforts to redesign the production of essential drugs like these, ensuring they remain safe, effective, and accessible for future generations.

Synthetic Routes of Paracetamol

Paracetamol is an amide that can be disconnected either to amine + acyl chloride or to amine + anhydride.



paracetamol

Figure 1: The hypothetical fragments of the disconnection of 1-butyne are an ethyl cation and an ethynide anion

In general, we call the fragments of a hypothetical retrosynthetic disconnection synthons. Seeing the synthons above may help us to reason that we could, in theory, synthesize a molecule of 1-butyne by combining an ethyl cation with an ethynide anion. We know, however, that bottles of carbocations and carbanions are not to be found on our laboratory shelves and that even as a reaction intermediate, it is not reasonable to consider an ethyl carbocation. What we need are the synthetic equivalents of these synthons. The synthetic equivalent of an ethynide ion is sodium ethynide, because sodium ethynide contains an ethynide ion (and a sodium cation). The synthetic equivalent of an ethyl cation is ethyl bromide.

Which reagent is best can often only be determined by experimentation—commercially, paracetamol is made from *para*-aminophenol and acetic anhydride largely because the byproduct, acetic acid, is easier to handle than HCl.

Synthesis I

An illustrative example of the environmental and operational limitations associated with traditional paracetamol synthesis is seen in the Hoechst-Celanese process, a widely cited industrial route. This method utilizes highly corrosive and toxic reagents, notably hydrofluoric acid (HF) and thionyl chloride ($SOCl_2$), both of which pose serious safety hazards to workers and require specialized equipment for containment and handling. Beyond the inherent risks of the chemicals involved, the process also demonstrates problems with chemical selectivity, leading to reduced yields and the need for additional purification steps. Moreover, the reaction relies on a homogeneous acid catalyst, which after use must be neutralized—typically with a base—thereby generating stoichiometric quantities of inorganic salt waste. This not only contributes to environmental burden but also increases the overall cost and complexity of waste management[35,36]. These drawbacks underscore the urgency of developing more sustainable and environmentally friendly synthetic alternatives, particularly those that minimize hazardous reagents, reduce waste output, and are compatible with modern green chemistry practices.

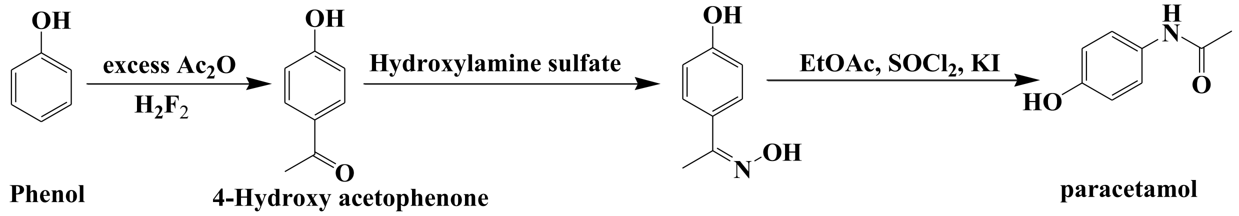


Figure 2: Beckman rearrangement of 4-hydroxy acetophenone

Synthesis II

One of the older methods employed for the synthesis of paracetamol involves the Bamberger rearrangement of phenylhydroxylamine, which is itself obtained through the nitration of benzene followed by reduction. This classical route, however, poses significant environmental and operational concerns. Notably, the reduction step demands the use of stoichiometric quantities of iron and strong acids, which results in the generation of substantial quantities of non-recoverable iron sludge and iron oxide waste. The management of such inorganic waste presents a major challenge, particularly in regions with strict environmental disposal regulations. Furthermore, the reaction pathway suffers from low selectivity, as the reduction of nitrobenzene often leads to aniline formation as a major by-product, thus reducing the overall efficiency and purity of the desired intermediate[37,38]. These limitations highlight the need for alternative synthetic approaches that begin with renewable, bio-derived raw materials and avoid the use of harsh reagents and environmentally burdensome processes.

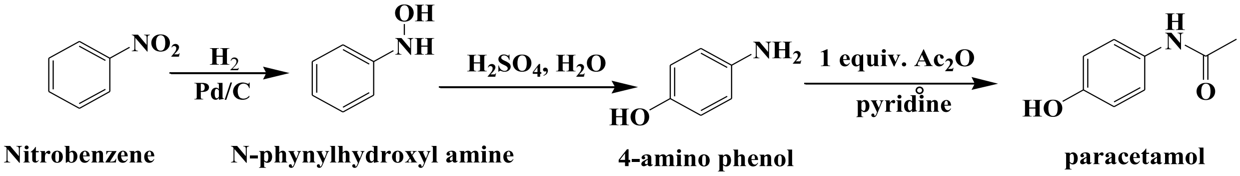


Figure 3: Bamberger rearrangement of phenylhydroxylamine

Modern synthetic strategies should be designed to align with the principles of green chemistry, minimizing hazardous waste, improving atom economy, and ensuring compliance with environmental norms, especially in countries where pharmaceutical manufacturing is closely regulated.

Synthesis III

In pursuit of more sustainable alternatives to conventional paracetamol synthesis, Andreas S. Bommarius and colleagues explored the feasibility of employing three phenol-derived compounds—hydroquinone, 1,4-benzoquinone, and 4-nitrophenol—as starting materials for the development of greener synthetic pathways. These compounds offer potential advantages due to their structural relevance and accessibility from renewable resources. Additionally, pathways traditionally involving phenol derived from benzene, such as those incorporating the Beckmann rearrangement, were also evaluated under the lens of renewability, particularly when the phenol feedstock is derived from biomass or other non-fossil sources[39].

A critical requirement for any new synthesis pathway is that it must be industrially feasible, demonstrating performance that meets or surpasses current methodologies in terms of Green Chemistry principles, such as atom economy, energy efficiency, and waste minimization[40]. Given the enormous global demand for paracetamol, priority was given to processes that are amenable to continuous flow systems, which are better suited to large-scale production[41]. Moreover, due to the drug's pharmaceutical application, high selectivity and product purity are of utmost importance, necessitating routes that minimize by-product formation[42].

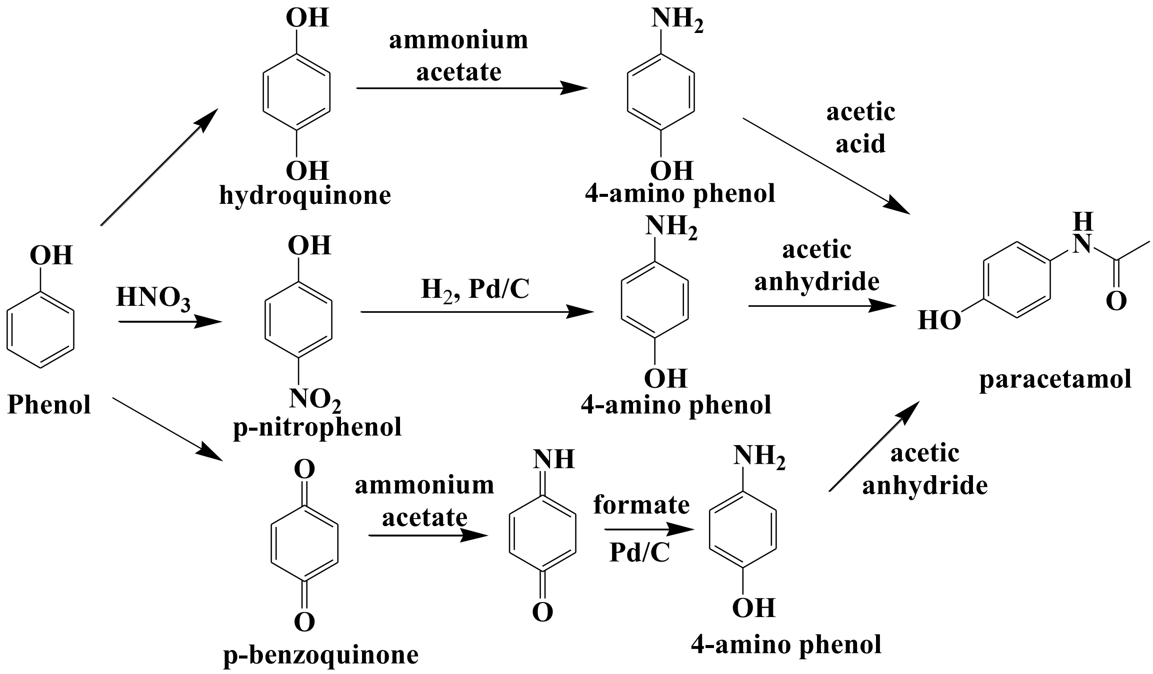


Figure 4: Sustainable pathways for paracetamol synthesis

The three proposed renewable-based pathways were systematically evaluated and compared not only with one another but also against four existing synthetic approaches—namely the Bamberger rearrangement, the Beckmann route, and two emerging bio-based strategies derived from β-pinene and p-hydroxybenzamide[43]. Each method was assessed on the basis of environmental impact, efficiency, scalability, and overall process viability. This comparative analysis aimed to identify the most promising routes that could potentially replace or supplement traditional production processes in a commercially sustainable and environmentally responsible manner[44].

Synthetic Routes of Ibuprofen

For aldehydes and most aliphatic ketones, the position of equilibrium favors cyanohydrin formation. For many aryl ketones (ketones in which the carbonyl carbon is bonded to a benzene ring) and sterically hindered aliphatic ketones, however, the position of equilibrium favors starting materials; cyanohydrin formation is not a useful reaction for these types of compounds[44]. The following synthesis of ibuprofen, for example, failed because the cyanohydrin was formed only in low yield.

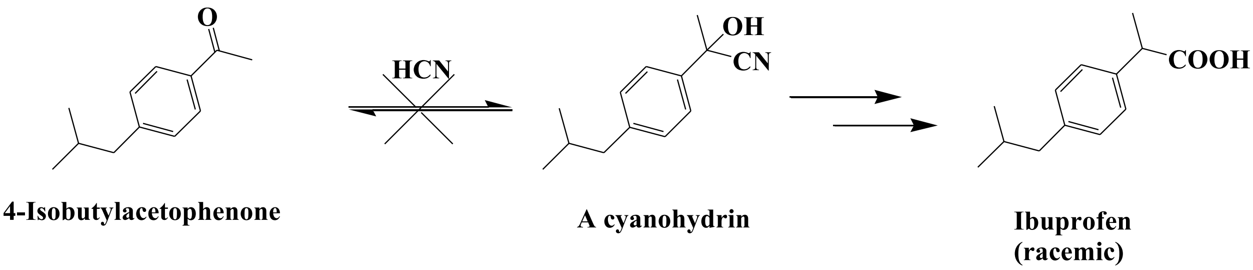


Figure 5: Low-yield cyanohydrin formation in ibuprofen synthesis

Reducing an alcohol involves converting the alcohol to the tosylate ester, then using a hydride reducing agent to displace the tosylate leaving group. This reaction works with most primary and secondary alcohols. Wade, page: 479

A major consideration in any industrial synthesis is atomefficiency; it is most efficient to use only reagents whoseatoms appear in the final product. An example of theevolution of syntheses with greater and greater atomefficiency is the industrial synthesis of ibuprofen[45].

Synthesis I

One of the earliest industrially adopted synthetic routes for the manufacture of ibuprofen, a widely prescribed non-steroidal anti-inflammatory drug (NSAID), was a multi-step process centered on the strategic introduction of a methyl substituent adjacent to the carboxylic acid moiety of 4-isobutylphenylacetic acid. This classical method, developed in the 1960s by Boots Pure Drug Company, represented a significant advancement at the time in large-scale organic synthesis, enabling the commercial availability of ibuprofen[46]. However, it also embodied many of the limitations of early pharmaceutical manufacturing in terms of environmental sustainability and atom efficiency.

The synthesis commenced with the Fischer esterification of 4-isobutylphenylacetic acid. In this step, the carboxylic acid was converted into its ethyl ester derivative by refluxing with ethanol in the presence of a strong acid catalyst, typically concentrated sulfuric acid. The purpose of esterification was twofold: it served to activate the molecule for subsequent carbon–carbon bond-forming reactions and also protected the carboxylic acid group under the strongly basic conditions of the next step.

The resulting ethyl ester underwent a crossed Claisen condensation with diethyl carbonate, using sodium ethoxide as the base. This transformation led to the formation of a β-keto diester intermediate (commonly referred to as compound B) via generation of a resonance-stabilized enolate. This intermediate possessed a central active methylene group, which is flanked by two electron-withdrawing carbonyl groups, significantly enhancing its acidity and reactivity. The stabilized enolate of compound B is then well-suited for electrophilic alkylation.

Subsequently, methyl iodide was introduced as the electrophilic methylating agent, allowing for the installation of the desired methyl group on the methylene carbon. This alkylation resulted in the formation of a disubstituted malonic ester (compound C). The two ester groups in compound C were then subjected to acidic or basic hydrolysis, converting them into carboxylic acids and yielding the corresponding disubstituted malonic acid (compound D).

The final step involved thermal decarboxylation of compound D. Upon heating, one of the carboxylic acid groups was lost as carbon dioxide, and the remaining structure was rearranged to furnish racemic ibuprofen—the target molecule. While this synthesis was robust and reproducible on an industrial scale, it required multiple unit operations, careful pH control during hydrolysis, and elevated temperatures for decarboxylation, all of which contribute to increased energy consumption and process complexity.

From a green chemistry perspective, this route is not atom-economical. Out of the 18 carbon atoms present in intermediate C, only 13 carbon atoms are retained in the final ibuprofen structure. The remainder are lost as waste[47], predominantly in the form of carbon dioxide and by-products generated during ester hydrolysis. Moreover, the use of stoichiometric quantities of toxic and corrosive reagents, such as methyl iodide and strong mineral acids, raises additional concerns regarding operator safety, waste management, and environmental impact.

This significant loss of carbon content and generation of inorganic and organic waste highlights one of the major drawbacks of early pharmaceutical synthetic methods. Though efficient in terms of yield and feasible for large-scale implementation, such processes lacked the sustainability and resource conservation considerations that are now central to modern chemical manufacturing. The inefficiencies of this traditional route have driven the development of newer, greener synthetic strategies that emphasize minimal step count, atom economy, waste reduction, and safer reagent profiles.

The transition from this early methodology to modern alternatives represents a paradigmatic shift in pharmaceutical chemistry—from maximizing yield alone to optimizing holistic process metrics, including E-factor, process mass intensity (PMI), and life-cycle assessment (LCA). The need for such improvement has been particularly acute in the context of active pharmaceutical ingredients (APIs) like ibuprofen, where global demand and high production volumes necessitate not just cost-effective, but also environmentally responsible synthetic technologies.

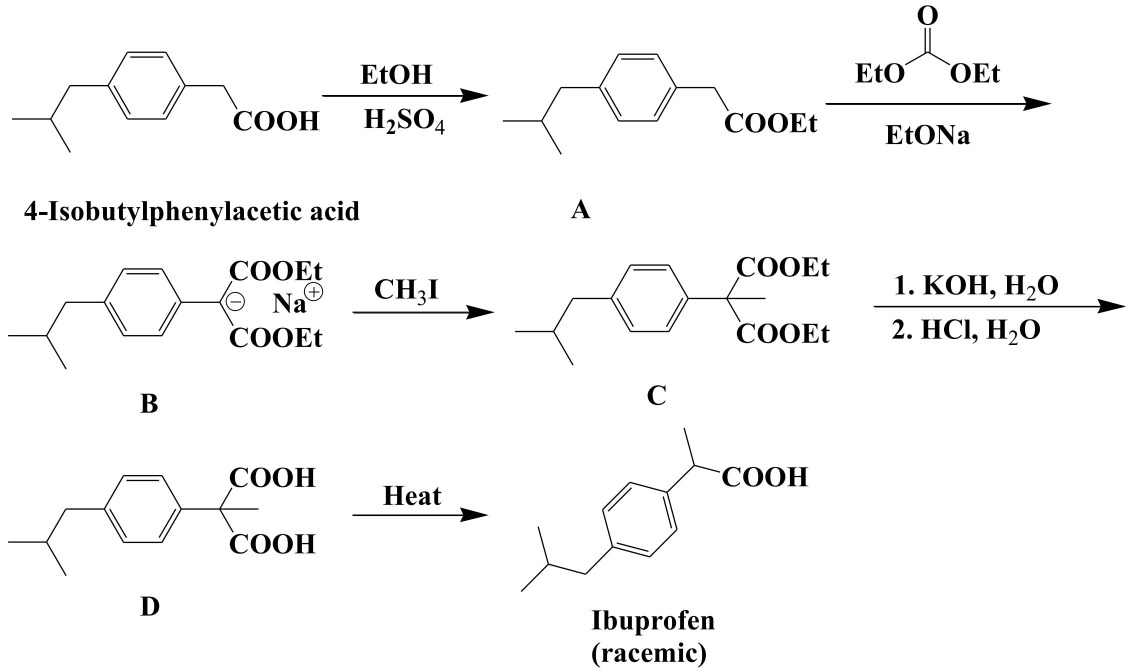


Figure 6: Classical multi-step synthesis of ibuprofen via esterification, Claisen condensation, methylation, hydrolysis, and decarboxylation—highlighting low atom economy and high waste generation

Synthesis II

An alternative synthetic route to ibuprofen that exhibits significantly improved atom economy and aligns better with the principles of green chemistry begins with 4-isobutylacetophenone as the starting material[48]. This method reduces the number of steps and minimizes waste by employing more direct transformations and avoiding stoichiometric use of hazardous reagents, making it more attractive for large-scale pharmaceutical manufacturing.

The first step in this sequence involves the reaction of 4-isobutylacetophenone with chloroacetonitrile in the presence of a strong base such as sodium ethoxide. This reaction results in the formation of an epoxynitrile intermediate (compound E) via nucleophilic addition and subsequent intramolecular epoxidation. The base facilitates the formation of the enolate of the ketone, which then undergoes alkylation with chloroacetonitrile, followed by cyclization to form the three-membered epoxide ring. The nitrile group introduced in this step serves as a latent carboxylic acid moiety that will later be unmasked during hydrolysis.

In the next step, compound E is treated with lithium perchlorate ($LiClO_3$), a Lewis acid catalyst, which promotes the rearrangement of the epoxide ring. The electrophilic lithium ion activates the epoxide oxygen, facilitating ring opening and rearrangement to yield an α-cyanoketone intermediate (compound F). This transformation is a key step, converting a strained heterocycle into a more stable, functionally rich intermediate capable of undergoing facile hydrolysis.

The α-cyanoketone group in compound F is chemically analogous to an acid chloride in terms of its reactivity toward hydrolysis. The adjacent carbonyl and nitrile functionalities activate the methylene group, making it susceptible to nucleophilic attack by water under acidic or basic conditions. Upon hydrolysis, compound F is converted into ibuprofen, with the nitrile group transforming into a carboxylic acid and releasing cyanide ion (CN^-) as a by-product. This step is particularly efficient, as it converts both functional groups into the desired carboxylic acid without requiring the use of harsh chlorinating agents or complex protecting group strategies[49,50].

This synthetic route stands out for several reasons. Firstly, it minimizes the number of reaction steps compared to the traditional synthesis. Secondly, the process utilizes carbon atoms more efficiently, resulting in a higher atom economy. In contrast to the original route, which involved significant loss of carbon content through decarboxylation and hydrolytic degradation, this pathway ensures that a greater proportion of the atoms from the starting materials are incorporated into the final ibuprofen molecule. The improved yield, reduced waste generation, and use of catalytic rather than stoichiometric reagents position this synthetic strategy as a more environmentally benign and economically favorable approach for ibuprofen production[51].

Overall, this route illustrates the advantages of modern synthetic design in pharmaceutical chemistry—integrating atom economy, functional group interconversion, catalytic processes, and mild reaction conditions to create a cleaner, safer, and more sustainable manufacturing protocol. It serves as a compelling example of how advances in organic synthesis and reaction engineering can transform the production of widely used drugs, aligning with both regulatory expectations and environmental sustainability goals[51, 52].

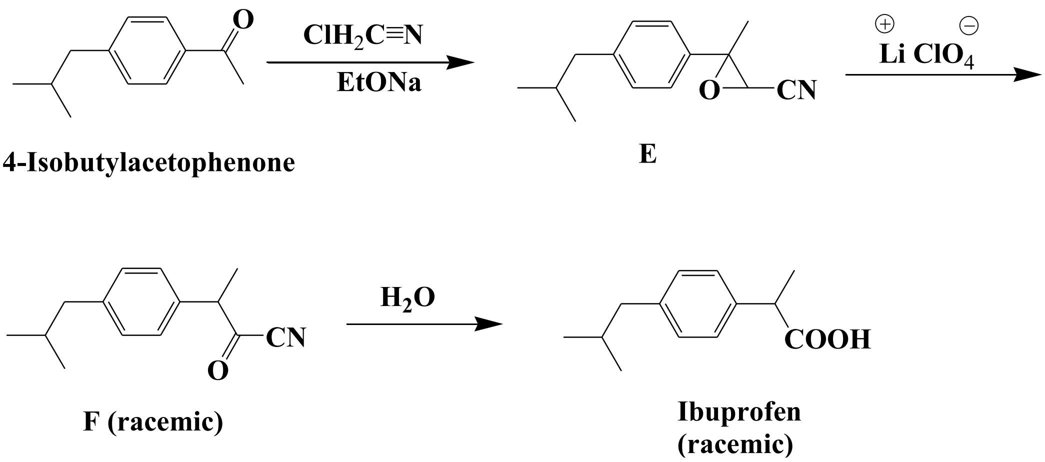


Figure 7: Green synthesis of ibuprofen starting from 4-isobutylacetophenone via epoxynitrile (E) and α-cyanoketone (F) intermediates—demonstrating improved atom economy, reduced steps, and enhanced sustainability

Synthesis III

The development of a more environmentally benign and industrially efficient synthesis of ibuprofen stands as a milestone in green chemical process innovation. This alternative, known as the "green route," was engineered by Boots–Hoechst–Celanese (BHC) Company in the United States and garnered international recognition for its contributions to sustainable industrial practices. In acknowledgment of its technological and environmental significance, the process was awarded the Kirkpatrick Chemical Engineering Achievement Award in 1993 and subsequently honored with the prestigious Presidential Green Chemistry Challenge Award in 1997[53].

The first step of this three-step synthetic sequence involves the acid-catalyzed Friedel–Crafts acylation of isobutyl benzene using acetic acid in the presence of hydrogen fluoride (HF), which acts as both solvent and catalyst. Remarkably, hydrogen fluoride in this context is fully recoverable and reusable, thereby minimizing environmental hazards and waste production. When the acetic acid formed as a by-product in this step is valorized for alternative industrial applications, the effective atom economy approaches 100%, reflecting a zero-waste ideal in line with green chemistry principles.

The second step involves the reduction of the intermediate aryl ketone to its corresponding secondary alcohol. This transformation is achieved through catalytic hydrogenation using Raney nickel, a finely divided, highly porous form of nickel alloyed with aluminum. Raney nickel is widely respected for its stability, high surface area, and robust catalytic performance under mild conditions. Importantly, this reaction proceeds with complete incorporation of all atoms into the product, yielding an atom economy of 100%. In the final stage, the synthesized alcohol undergoes carbonylation to yield ibuprofen. This reaction is catalyzed by palladium (Pd) complexes, known for their excellent turnover efficiency and recyclability in carbon–carbon bond-forming reactions. Like the previous steps, this transformation is conducted under mild and controlled conditions and generates no stoichiometric waste, thereby achieving an ideal atom economy of 100%. Collectively, the BHC green route exemplifies the transformative impact of green chemistry in pharmaceutical manufacturing. The process not only reduces the number of synthetic steps—from six in the traditional route to three—but also minimizes waste, improves yield, and eliminates the need for hazardous reagents such as aluminum trichloride, hydrochloric acid, and stoichiometric bases. Additionally, the catalyst systems used in the green process (HF, Raney nickel, and Pd) are all recoverable, recyclable, and operate under environmentally benign conditions. This synthesis route has become a textbook example of green process design, illustrating how conventional multi-step procedures with poor atom economy can be re-engineered into streamlined, efficient, and environmentally responsible alternatives. It underscores the feasibility of scaling up green chemistry principles to meet the demands of large-volume drug production, without compromising cost, performance, or safety. The BHC ibuprofen process remains a benchmark for future developments in the design of sustainable pharmaceutical processes.

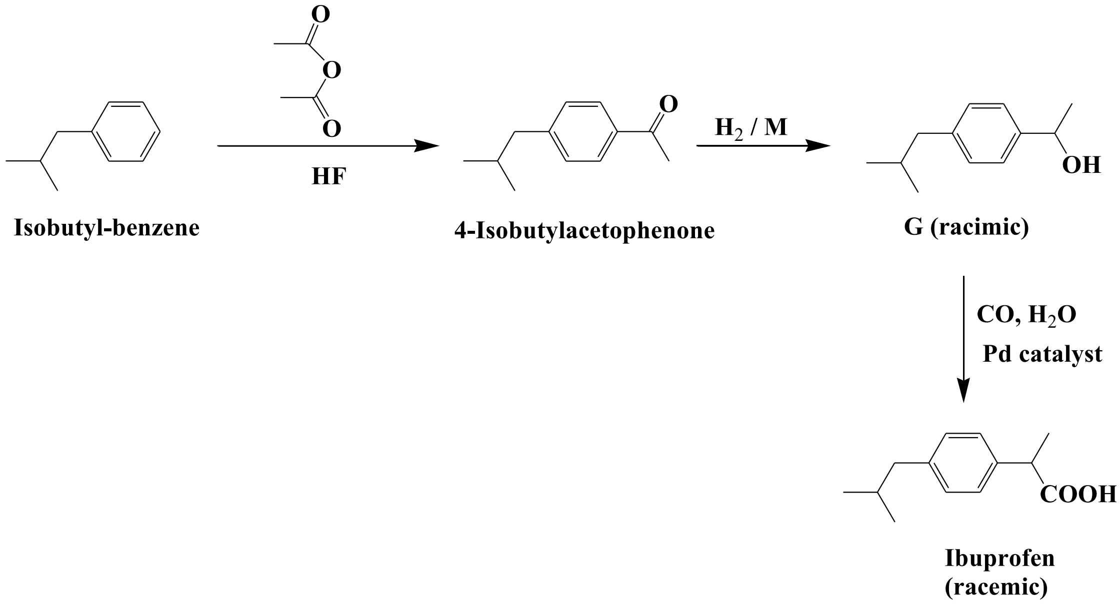


Figure 8: Sustainable Ibuprofen Synthesis via the BHC Process: Fewer Steps, Cleaner Chemistry

The ultimate in atom efficiency in the synthesis of ibuprofen is achieved in the following synthesis. Catalytic reduction of the carbonyl group of 4-isobutylacetophenone gives the alcohol G. Palladium-catalyzed carbonylation of G gives ibuprofen. The one carbon atom introduced in the synthesis appears in the final product!

Conclusions:

The synthesis of paracetamol has undergone significant evolution over the decades, transitioning from early methods that involved hazardous reagents and low selectivity to more environmentally conscious approaches aligned with the principles of green chemistry. Traditional industrial processes such as the Hoechst-Celanese and Bamberger routes, though effective at scale, pose considerable environmental and operational challenges—including the use of corrosive chemicals and the generation of large amounts of inorganic waste. These drawbacks have driven the need for alternative synthetic pathways that are both ecologically benign and industrially viable.

Recent advancements in paracetamol synthesis focus on the utilization of renewable phenol-based feedstocks, such as hydroquinone, benzoquinone, and especially 4-nitrophenol. Among these, the 4-nitrophenol route has gained prominence for its high efficiency, excellent selectivity, and compatibility with continuous processing systems. Comparative studies suggest that such renewable-based approaches not only offer improved atom economy and reduced hazardous by-products but also enhance process safety and sustainability. These innovations are critical to decentralizing paracetamol production, addressing global demand, and meeting increasingly stringent environmental regulations.

Similarly, the conventional synthesis of ibuprofen—originally comprising six chemical steps—has been scrutinized under the lens of green chemistry due to its inefficiencies, including high energy requirements, use of hazardous reagents, and significant waste generation. In response, the Boots–Hoechst–Celanese (BHC) process was developed as a streamlined, environmentally superior alternative. This modern three-step synthesis employs recyclable catalysts and solvents, generates fewer by-products, and operates under milder, energy-efficient conditions.

The BHC route not only improves the sustainability of ibuprofen manufacturing but also serves as a benchmark for the application of green chemistry in the pharmaceutical industry. Its success highlights how process redesign can enhance both environmental and economic performance at industrial scale.

Overall, the evolution of synthetic routes for both paracetamol and ibuprofen reflects the pharmaceutical industry's broader shift toward greener, safer, and more sustainable practices. Embracing these innovations is essential to reducing environmental impact, ensuring global drug availability, and aligning pharmaceutical production with the goals of responsible industrial development in the 21st century.

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OPTIMIZING AGRICULTURAL DRYING: A COMPREHENSIVE ANALYSIS OF BOX-TYPE SOLAR DRYERS

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Abstract:

This study explains the use and performance of box-type solar dryers for preserving agricultural food products using solar energy. The solar dryer works on the greenhouse effect, where solar energy heats the air inside, promoting moisture evaporation from the products. This chapter compares box-type solar dryers with traditional open sun drying, highlighting advantages, disadvantages and limitations of box-type solar dryers. The study also explains the construction, working principle, and various parts of box-type solar dryers. Experimental observations on drying onion and curry leaves show remarkable moisture reduction and drying rates. The study concludes that solar drying is a cost-effective, eco-friendly method for food preservation.

Keywords: Box Type Solar Cooker, Solar Energy, Renewable Energy, Greenhouse Effect, Eco-Friendly Cooking, Energy Conservation.

1. Introduction:

Drying is one of the methods used to preserve food products for longer periods. The heat from the sun coupled with the wind has been used to dry food for preservation for several years. Drying is the oldest preservation technique of agricultural products and it is an energy intensive process. High prices and shortages of fossil fuels have increased the emphasis on using alternative renewable energy resources. Drying of agricultural products using renewable energy such as solar energy is environmentally friendly and has less environmental impact.

Different types of solar dryers have been designed, developed and tested in the different regions of the tropics and subtropics. The major two categories of the dryers are natural convection solar dryers and forced convection solar dryers. In the natural convection solar dryers, the airflow is established by buoyancy induced airflow while in forced convection solar dryers the airflow is provided by using fan operated either by electricity or solar module or fossil fuel.

Solar thermal technology is a technology that is rapidly gaining acceptance as an energy saving measure in agriculture application. It is preferred to other alternative sources of energy such as wind and shale, because it is abundant, inexhaustible, and non-polluting. Solar air heaters are simple devices to heat air by utilizing solar energy and it is employed in many applications requiring low to moderate temperature below 80°C, such as crop drying and space heating. This chapter explains the details of box type solar dryer.

The objectives of the present study are given below

- To study the basic concept and working principle of a box type solar dryer.

- To understand the construction and components of a box type solar dryer.
- To analyze the drying process using solar energy.
- To compare solar drying with traditional open sun drying.
- To study the advantages and limitations of box type solar dryers.
- To promote the use of renewable energy for food preservation.

2. Classification of Solar Dryer

All the drying systems can be classified primarily according to their operating temperature ranges into two main groups of high temperature dryer sand low temperature dryers. However, dryers more commonly classified broadly according to their heating sources into fossil fuel dryers (more commonly known as conventional dryer) and solar-energy dryers. Strictly, all practically realized designs of high temperature dryer are fossil fuels powered, while the low temperature dryers are either fossil fuels or solar-energy based systems.

Solar dryers can be classified primarily according to their heating modes and the manner in which the solar heat is utilized in broad terms; they can be classified into two major groups, namely

- Active solar-energy drying systems (most types of which are often termed hybrid solar dryers)
- Passive solar-energy drying systems (conventionally termed natural-circulation solar drying systems).

There are three distinct sub- classes of either active or passive solar drying systems can be identified which vary mainly in design arrangement of system components and the mode of utilization solar heat, namely

- Integral- type solar dryers
- Distributed-type solar dryers and
- Mixed-mode solar dryers.

Natural Convection Cabinet Solar Dryer of Direct Gain Type:

- A cabinet type solar dryer consists of an enclosure with a transparent cover as shown in Figure.
- Openings are provided at the bottom and top of the enclosure for natural circulation.
- The material to be dried, is spread on perforated trays.
- Solar radiation enters the enclosure and it is absorbed by "the product as well as surrounding internal surfaces of the enclosure". Since the products are directly heated by solar radiations, we say that, the products get direct solar heat. Therefore, the solar dryer is known as direct gain type.
- Consequently, moisture from the product evaporates as the air Inside is heated. As temperature of air Increases, its density decreases therefore, low dense air moves upwards and leaves through the openings provided at the top of cabinet dryer. And, at the same times,

the comparatively cold atmospheric air having large density enters the cabinet dryer from openings provided at the bottom. Thus, natural convection occurs'

- The temperature inside the cabinet ranges from 50°C to 75°C and the drying time for products like dates, grapes, apricots, cashew nuts and chills varies from 2 to 4 days.

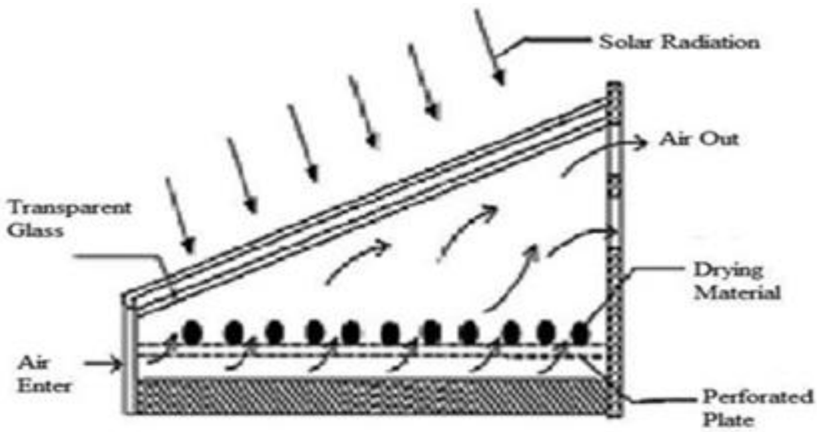


Figure 1: Natural Convection cabinet Solar Dryer of direct gain type

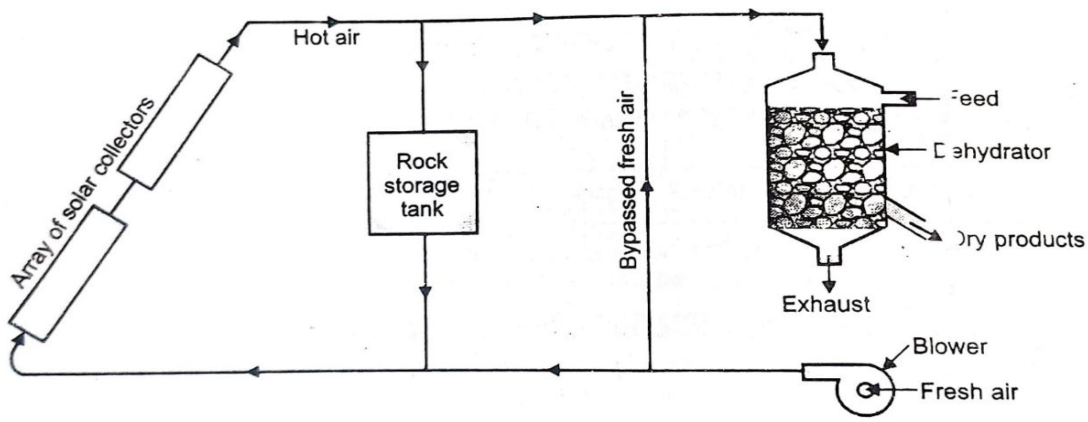


Figure 2: Forced Convection Solar dryer of Indirect Type

Forced Convection Solar Dryer of Indirect Gain Type

- Figure shows the schematic diagram of a forced convection solar dryer of indirect type. In this system, a blower is employed to make convection faster and efficient than natural convection cabinet solar dryer studied in previous sub article.
- Also, in case of natural convection cabinet solar dryer, it is not possible to regulate and control the temperature of products being directly exposed to solar radiation.
- In this forced convection solar dryer, a thermal storage is used to control the temperature of drying products.
- Here, a blower is used to circulate the atmospheric air through array of solar collectors. Due to solar radiations incident on the solar collectors, the air gets heated, while circulating through solar collectors.
- This heated air is supplied to dehydrator for the purpose of drying the products. The excess hot air is sent to sock storage tank, where it can be stored.

- The temperature of hot air passing through the dehydrator can be controlled by admitting fresh air through opening adjustments of dampers and temperature controllers. After drying the products, the hot and humid air is exhausted to the atmosphere.
- In this case, solar radiations do not come in direct contact with products. Therefore, we say that, the products did not get direct solar heat. Therefore, the solar dryer is known as indirect gain type.

3. Different Types of Solar Dryers

Basically, there are two types of solar dryers.

1. Integrated Solar Dryers
2. Distribution Solar Dryers
3. Box type Solar Dryers

Box Type Solar Dryer

The box- dryer's solar dryers have been widely used for small scale food drying. It consists of a wooden box with a hinged transparent lid. The inside is painted black and the food supported on a mesh tray above the dryer floor. Air flows into the chamber through holes in the front and exits from vents at the top of the back wall. Pioneering works on solar cabinet dryers were reported by the Brace Research Institute, Canada. The fundamental features of the standard Brace institute solar cabinet dryer. Brace type dryers achieve higher temperatures, and thus shorter drying times, than tent dryers. Drying temperatures in excess of about 80°c were reported for the dryer.

Construction of Box Type Solar Dryer

a) Outer Box
- Made of wood, metal sheet, or plywood
- Acts as a protective casing
- Painted black on the inside to absorb maximum solar radiation

b) Transparent Cover
- Made of glass or transparent polythene sheet
- Placed on the top of the box
- Allows sunlight to enter while reducing heat loss (greenhouse effect)

c) Drying Trays
- Made of wire mesh, bamboo, or perforated metal
- Placed inside the box in layers
- Hold the material to be dried and allow air circulation

d) Air Inlet and Outlet Vents
- Air inlet holes at the bottom or sides
- Air outlet vents at the top or rear
- Facilitate natural air movement (natural convection)

e) Insulation

- Provided between inner and outer walls using thermocol, sawdust, or glass wool
- Reduces heat loss

f) Absorber Plate (optional)

- Black-painted metal sheet placed at the bottom
- Increases heat absorption

Figure 3: Box Type Solar Cooker

Working Principle

- Solar radiation passes through the transparent cover.
- The black inner surfaces and absorber plate absorb heat and raise the internal temperature.
- The air inside the dryer gets heated and becomes lighter.
- Hot air rises and moves towards the outlet vent.
- Fresh air enters through the inlet vent, creating continuous air circulation.
- Moisture from the product evaporates due to heat.
- Moist air escapes through the outlet vents.
- Drying continues until the desired moisture level is achieved.

Advantages, Disadvantages and Limitations of Solar Dryer

a) Advantages

- **Low cost**: Simple construction using locally available materials.
- **No fuel or electricity required:** Operates completely on solar energy.
- **Eco-friendly:** Produces no pollution and reduces dependence on fossil fuels.
- **Better quality drying**: Protects products from dust, insects, birds, and rain compared to open sun drying.
- **Easy to operate:** Requires minimal skill and maintenance.
- **Improved** drying efficiency**:** Higher temperature than open sun drying due to greenhouse effect.
- **Suitable for small-scale use**: Ideal for farmers, households, and small food processing units.

b) **Disadvantages**

- **Weather dependent:** Drying rate decreases during cloudy or rainy conditions.
- **Slow drying rate:** Uses natural air circulation; drying is slower than forced or mechanical dryers.
- **Limited capacity:** Can dry only a small quantity of material at a time.
- **Uneven drying:** Products may require frequent turning or rearranging of trays.
- **No temperature control:** Temperature cannot be precisely regulated.
- **Not suitable for large-scale drying:** Unsuitable for commercial or industrial-level processing.

c) Limitations

- Dependent on weather conditions
- Slower drying during cloudy days
- Initial construction cost
- Limited control over temperature in simple designs.

4. Experimental Procedure

Step 1: Preparation of Sample

- Select fresh and uniform agricultural produce.
- Wash thoroughly with clean water.
- Slice into uniform thickness (3–5 mm).
- Record initial weight (W_1) of the sample using weighing balance.

Step 2: Setup of Solar Dryer

- Place the solar dryer in an open area facing the sun.
- Adjust the tilt angle of the solar collector according to local latitude.
- Ensure proper airflow through inlet and outlet vents.
- Place thermometer and hygrometer inside the drying chamber.

Step 3: Loading the Dryer

- Spread the sample uniformly on drying trays.
- Avoid overlapping of slices.
- Insert trays into the drying chamber.
- Close the dryer properly.

Step 4: Drying Operation

- Start the experiment at peak sunlight hours (10:00 AM – 4:00 PM).
- Allow hot air to circulate naturally or using a solar-powered fan.
- Record readings of drying chamber temperature, Relative humidity, Weight of sample at regular intervals (every 30 or 60 minutes)
- Rotate trays periodically for uniform drying.

Step 5: Termination of Drying

- Continue drying until weight becomes nearly constant and Product becomes brittle or leathery
- Record final weight (W_2).
- Switch off fan (if used) and remove trays.

Step 6: Cooling and Storage

- Allow dried samples to cool to room temperature.
- Store in airtight containers.
- Observe texture, colour, and aroma.

Precautions

- Do not overload trays
- Avoid cloudy or rainy days
- Maintain uniform slice thickness
- Ensure proper ventilation

5. Observations

Sample 1: Onion

Initial weight of onion (M_I) = 140 gm

Table 1: Variation of weight of onion

Sr. No.	Time	Temperature (°C)	Weight (gm)
1.	10.00 am	25	140
2.	10.30 am	28	134
3.	11.00 am	30	130
4.	11.30 am	35	125
5.	12.00 pm	41	118
6.	12.30 pm	47	100
7.	1.00 pm	55	86
8.	1.30 pm	57	67
9.	2.00 pm	60	62
10.	2.30 pm	63	51
11.	3.00 pm	66	45
12.	3.30 pm	70	38
13.	4.00 pm	70	38

Calculations

Initial weight of given material (M_I) = 140

Final weight of given material (M_d) = 38

a) Moisture Constant (M_c) = $\frac{M_I - M_d}{M_I} \times 100$

= $\frac{140-38}{140}$ ×100 = 72.8 gm

b) Drying Rate (R_d) = $\frac{M_I - M_d}{T}$

Time T =$t_1 - t_2$, t_1=10.00 and t_2=4.00

Drying Rate (R_d) = $\frac{M_I - M_d}{T} = \frac{140-38}{10.00-4.00}$ = 17 gm/hr

Sample 2: Curry Leaves

Initial Weight of Curry Leaves (M_I) =150 gm

Table 2: Variation of weight of Curry Leaves

Sr. No.	Time	Temperature (°C)	Weight (gm)
1.	10.00 am	25	150
2.	10.30 am	28	146
3.	11.00 am	30	138
4.	11.30 am	35	125
5.	12.00 pm	41	118
6.	12.30 pm	47	100
7.	1.00 pm	55	86
8.	1.30 pm	57	81
9.	2.00 pm	60	70
10.	2.30 pm	63	63
11.	3.00 pm	66	58
12.	3.30 pm	70	41
13.	4.00 pm	72	36

Calculations

Initial weight of given material (M_I) = 150 gm

Final weight of given material (M_d) = 36 gm

a) Moisture Constant (M_c) = $\frac{M_I - M_d}{M_I} \times 100$

$M_c = \frac{150-36}{150}$ x 100 = 76.00 gm

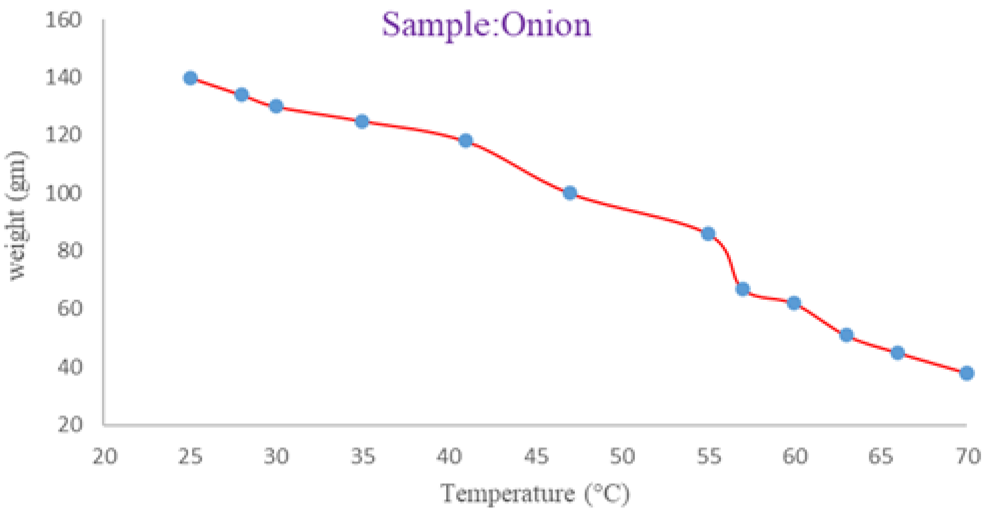
b) Drying Rate (R_d) = $\frac{M_I - M_d}{T}$

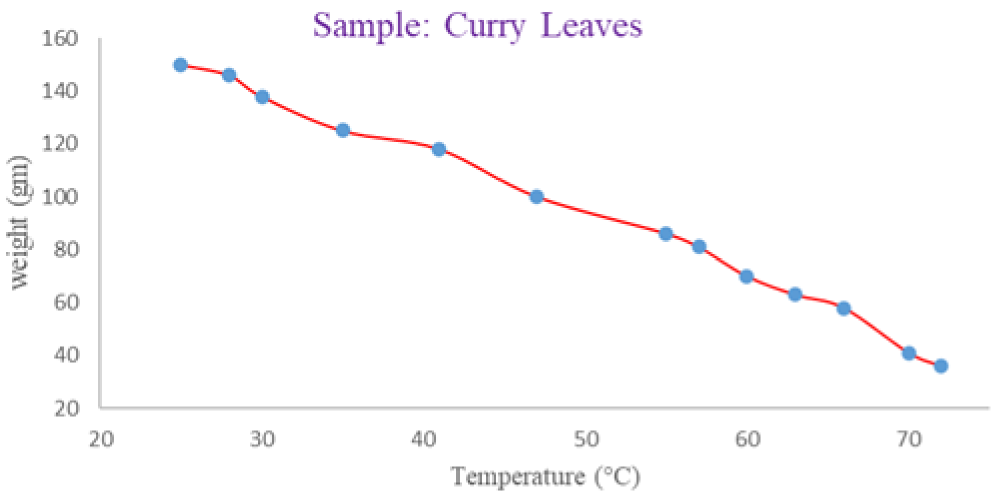
Here, Time T = $t_1 - t_2$, t_1=10.00 am and t_2=4.00 pm

Drying Rate $(R_d) = \frac{M_I - M_d}{T} = \frac{150-36}{10.00-4.00}$ =19 gm/hr

6. Result and Conclusion:

For Onion the Moisture Constant (M_c) is 76.08 and Drying Rate (R_d) is 17 gm/hr. and for Curry Leaves the Moisture Constant (M_c) is 76 and Drying Rate (R_d) is 19 gm/hr. Solar drying is an effective, economical, and environmentally friendly method for food preservation. The variation of weight with respective to temperature for both the sample are shown below.





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DESIGN AND IMPLEMENTATION OF REMOTELY LOCATED ENERGY METER MONITORING WITH LOAD CONTROL AND MOBILE BILLING SYSTEM

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Abstract:

As the demand of having reliable power grows, as well as the demand of having sustainability energy, reliable monitoring and billing solutions have become necessary. The traditional billing systems are still based on manual readings that are usually not accurate, take time and fail to deliver real time insights. This proposal involves coming up with a design and implementation of a remotely positioned energy meter monitoring system (including load control) with mobile billing, solar integration, and enhanced safety measure. This system is constructed based on a microcontroller of ESP8266 – Node MCU that gathers consumption rates with the help of a current sensor and shows the results on a local LCD screen. Data on usage is sent to an IoT web page and sent to the users over a GSM modem allowing monitoring and automatic billing. A relay module will offer load control which means that it is possible to disconnect or reconnect remotely supply depending upon its use or payments or demand control. The hybrid power system also allows using the power source based on hybrids: when the sun rays are present the meter is switching to the solar source and thus limiting the dependence on the grid and encouraging the use of renewed energy sources. The design is enhanced with fire and gas leakage sensors to create greater safety by responding to and disconnecting loads during dangerous scenarios with immediate alerts. Customers are also informed in real-time via SMS on the usage, billing, switching of source and safety messages. The solution being proposed is able to not only remove the manual meter reading, but also enhances the precision of billing, security of the user as well as offering a savvy solar-grid control, and also offers a model that can be extended by near future smart energy systems in residential, commercial and industrial settings.

Keywords: Smart Energy Meter, IoT Based Monitoring, Remote Meter Reading, Load Control, relay Module, Solar Integration, Renewable Energy, Hybrid Power System, Sustainable Power System, Smart Grid.

1. Introduction

The increased need of sustainable and efficient energy management in the world has enhanced the adoption of Artificial Intelligence (AI) in smart grid applications. A Smart Energy Meter that is AI-Enhanced is the next-generation device that will assist in minimizing the use of power, increasing the reliability of a particular product, and eventually moving towards renewable energy infrastructure. Not only does this system measure and monitor the amount of energy used within real time, but it also uses the algorithms of AI to predict the demand of energy, control the distribution of loads, and avoid actions that lead to the waste of power. The meter provides a smooth supply of energy by combining both solar energy sources and a traditional grid infrastructure that intelligently switches between the solar and grid energy supply depending on its demand and availability. Predictive load control is included to enable the system to predict the patterns of consumption and automatically regulate usage in order to ensure efficiency and minimize peak load stress. Moreover, safety and operating reliability are improved by the hazard recognition system and warning devices including overload, short-circuit, or fire warning devices. Altogether, the AI-Enhanced Smart Energy Meter will represent a revolutionary solution to the contemporary energy management as it is a blend of data analytics, machine learning, and IoT-based communication. Not only does it enable the consumers to track and manage their use of energy in an effective and efficient way, but it also helps in shaping a smarter, cleaner and more resilient energy system

2. Literature Review

The article by Ahmad and Zhang (2020) examines the implementation of the Internet of Things (IoT) in the smart energy metering and demand response. The paper explains the ability of IoT-based smart meters to monitor, data collection and analysis of energy usage in real time that translate to efficient energy management. The system supports dynamic demand response, which means it will automatically tune down or turn up the use of energy based on the conditions in the supply. This strategy contributes to the sustainability of energy consumption, grid reliability, and the decrease of the carbon emission through the maximization of energy delivery and consumer education. In this study, there are various advantages, such as energy efficiency, cost saving, grid stability, and decision-making endeavors that can be made based on real-time data analytics. Other challenges which are identified concerning IoT devices have been highlighted in the paper as high costs of initial installation, data security, and interoperability. Also, a strong connectivity of the network and the cost of managing big data are two significant constraints. According to the authors, these technical and security issues are important to be resolved in order to realize the large scale adoption of the IoT-based smart energy systems.

In the paper by Rajesh and Balaji (2018), the authors present the work about the IoT-based real-time energy monitoring system using the modules of Node MCU and GSM to effectively control the energy consumption. The first idea consists of allowing users to remotely track electricity usage under the use of IoT technology. To send sensor data on power usage real-time to the users, the Node MCU microcontroller is able to collect power usage data via sensors and then sends it over the GSM network. This design has removed the manual reading of the meters, and the instantaneous update on the consumption and the associated cost via mobile communication will improve transparency and awareness of the user of their levels of energy use. It enhances less human error in the billing process, conserves energy and offers cost effective connection system by use of GSM technology. Its architecture is easy to use and can be realized in both domestic and commercial locations. Network connectivity determines the accuracy and performance of the system and any failure of the GSM service can slow the data transmission. Moreover, the use of cloud data creates issues of security and privacy concerns. The research primarily covers the small scale testing and not the large scale integration and interoperability with the smart grids. The future would bring better data encryption, scaled up to higher levels and compatibility with renewable energy systems.

Sultana and Roy (2021) paper introduce a combination scheme of renewable energy sources with smart meters infrastructures to enhance energy management. It has a fundamental idea of uniting distributed renewable production (solar or wind) with sophisticated metering equipment (smart meters) that both observe consumption as well as feed generation information back to the grid and permit dynamic energy-management schemes. This synergy enables the system to align generation and consumption in a more effective manner, reduce consumption of wasted energy and give a better insight of supply as well as demand dynamics. The integrated approach will increase efficiency as locally generated renewable power is captured and used instead of wholly relying on the grid. It also provides granular data provided by smart meters, empowers consumers and utilities and allows them to make dynamic adjustments, demand response and enhance grid-stability. It goes also in line with sustainability ambitions by increasing the proportion of clean energy. Nevertheless, it is only possible to solve the problem with considerable infrastructure improvements: much of the renewable generation infrastructure, as well as smart metering, will need to go large-scale. Initial levels of investment and complexity of integrating the system could be high. Moreover, the fluctuation and non-reliability of renewable sources may make it difficult to schedule and provide consistent supply with either no or inadequate storage or predictability. In the study, the primary aim is conceptual architecture and simulation, but not a real-world large-scale implementation in a diverse grid perspective. It does not adequately cover security/privacy issues of smart-meter data and is not detailed in the discussion of grid-edge behaviours in high renewable penetration. Future research might be aimed at field tests, energy storage and prediction integration, and cyber but also regulatory threats.

The article by Rajeswari and Kumari (2019) revolves around the construction of smart energy metering system that incorporates the use of GSM and IoT systems to automate the billing and allow the power to be controlled. The principle idea of the research is to substitute the obsolete energy meters with the smart system able to monitor the energy in real time, generate the bills automatically, and control the loads remotely. The suggested system involves sensors and microcontrollers to gauge energy usage and forward the results to the consumers and power supply companies by use of the GSM network. Consumers can use IoT connectivity to get details of how they use it and billing information via web or mobile app thereby enhancing transparency and efficient use of energy. The system will automate the billing process eliminating human errors and time loss during the manual reading of the meter. It gives real time gibtigs on energy use, allows loads to be remotely cut off in case of excessive use, and it facilitates more complete control of demand side. It needs a stable internet and GSM connection whose effectiveness varies in some areas. Moreover, the installation can be expensive to the small-scale consumers, even though the work primarily represents a prototype, but does not consider large-scale implementation, cybersecurity, and interaction with the renewable energy system. The future study can cover the data protection, scalability, and more efficient interoperability with smart grids.

The SIM Com Wireless Solutions (2016) SIM800 Series AT Command Manual is the technical manual on how to operate and program the SIM800 GSM/GPRS module. The manual explains the AT controls that are needed to program and manage different operations of the SIM800 module, which includes, sending and receiving, SMS, making calls, internet connection through the GPRS, management of power and network. It guides the developers and engineers on the required guidelines to implement the GSM communication features of the IoT and embedded systems in a manner that works. The manual is critical in using wireless communication in such devices as smart meters, home automation systems, and remote monitoring applications and with this, the manual provides clear, structured and detailed instructions to each command and thus developers can easily adopt GSM based functionalities. It supports various communication options, has the capability to be customized, and works out with many types of microcontrollers. The manual requires pre-existing knowledge of AT commands and embedded systems which is why it is not as accessible to new users. Moreover, there are certain complex features that can be updated with the firmware or need further configuration, which is the central topic of the document, and does not show the practical example of the implementation or troubleshooting advice. Future changes may have improved illustrations, ways of handling errors, and the better way of integrating with modern system of the Internet of things.

This project uses ESP8266EX Wi-Fi SoC (Espress if systems, 2019), which is very popular in IoT and embedded systems applications according to ESP8266EX Datasheet. The paper describes the architecture, features, pin layout, power management and communication interfaces of the chip. The ESP8266EX is a combination of high-performance Tensilica L106 processor, inbuilt Wi-Fi, and low power usage which makes it appropriate to real-time and wireless network of communication. The datasheet is an important tool to developers working on designs of IoT-based devices, including smart meters, home automation systems, and remote sensors, to provide useful information on how to design the hardware and writes the correct firmware to reduce the external communication modules requirement. It has an option of different interfaces such as UART, SPI, and I2C that make it easy to connect it to add sensors and controllers. It is small in size, and has limited community support, which is more problematic for programming prototype and large-scale IoT applications than much more modern boards such as the ESP32. It does not have an inbuilt Bluetooth as well. The datasheet has most of the hardware specifications, and lacks extensive software development instructions. Subsequent task might consist of improved records on optimization of the firmware and increased the interoperability information.

Yadav and Patel (2020) propose the use of an IoT-based smart energy meter that would allow monitoring the load in real-time and provide safety alerts. The study in question is based on the primary idea of advancing the conventional metering systems with the use of such a tool as the IoT to provide the opportunity to observe the metering system remotely and transmit data automatically, as well as maintain the safety. The system, which has been proposed is one that constantly monitors the energy-consumption and load status and this information is then relayed to users and utility providers through a system of an online platform. The system is able to send instant warnings in the event of unusual load changes or electrical malfunctions to avoid risks like faulty short circuiting or breaking of equipment. This methodology enhances efficiency, safety, and the management of power that can be monitored and their capabilities to give a safety alert in order to minimize the chance of power outages. It increases the level of transparency in energy consumption and helps to live remotely with the help of the IoT, which enables users to track energy consumption anywhere. It is also what helps in effective management of loads and energy savings. High-quality internet connections are vital to the functioning of the system, and any breakout in the network can influence the transfer of data. The residential consumers can also find hardware and installations to be on the higher side. The analysis is mainly on implementing prototypes but is not large scale. It is not very comprehensive concerning data security, scalability, and sustainability of the system in the conditions of varying conditions.

Documentation provided by Arduino.cc (2023) explaining the interface between current sensors (ACS712/CT) and microcontrollers gives comprehensive information on how to connect and use current sensors to measure electrical current when operating in different applications. Its central idea is to connect ACS712 or Current Transformer (CT) sensors to the microcontrollers based on

Arduino and provide the real-time monitoring of the current. The resource gives the operation of sensors, example of wiring, methods of calibration and a code example of correct current measurements. The data can be used in the creation of IoT connected energy monitoring systems, smart meters, and home automation projects, in which the current flow needs to be displayed to manage power consumption and prevent accidents. The documentation provides a concise and realistic detail that can be used by both beginners and developers. It allows correct current recording, interfacing with simplicity and can be compatible with various microcontrollers. ACS712 and CT sensors are low cost and small in size and therefore suitable in education, prototyping and small-scale industrial projects due to the fact that their accuracy may be compromised by changes in temperature, noises, and calibration errors. Also, ACS712 sensors are not as sensitive and have small current range as the industrial sensors. The resource concentrates throughout on fundamental interfacing and lacks sophisticated information on signal conditioning, fault remedying, and interface with cloud-based internet of things (IoT). Enhancements in the course of the future may include better accuracy methods and more descriptions of real-world implementation.

IEC 62053 standard, defined by the International Electrotechnical Commission (IEC) (2019) is an accuracy and performance standard of the electricity meter equipment connected with the residential, commercial, and industrial use. The document has the methods of testing, the calibration of meters and the classification procedures of meters that measure active and reactive energy. It is confident that energy meters are of international standard of reliability, accuracy and safety. Aspects covered by the standard include electrical properties, environmental and mechanical stability, which offers a framework of uniformity and interoperability of energy meters throughout the globe, that the devices are in compliance with rigorous performance and safety standards. It assists manufacturers in staying within the same quality, consumer confidence, and good practices of billing and energy management. The standard can also be easily used to trade internationally and be approved by the regulation.The small manufacturers will find it difficult to adopt the IEC 62053 because it may raise production and testing expenses. Following rigorous technical specifications also can restrict the scope of design tube innovation. The standard mainly emphasizes the parameters of accuracy and performance and is silent on new technology developments as far as the internet of things-based smart metering or data communication protocols are concerned. It might undergo further updates in the future to encompass cybersecurity, interoperability with smart grids, and the digital data management components.

3. Proposed System

The proposed system will overcome the shortcomings of the conventional and semi-automated energy meters since it will offer a smart remotely monitored and safety-enabled energy management solution. It is based on the structure of a Node MCU (ESP8266) microcontroller, which is the main controller responsible for surveillance, communication and load control. One of the current sensors constantly keeps analogue of the energy used and the usage is indicated at the location local to a LCD screen to allow the user to view it. Meanwhile data on the consumption is relayed to an IoT web page by Wi-Fi to allow remote monitoring, and a GSM modem is used to relay the consumption data in the form of an SMS directly to the mobile phone of the user as well as to provide billing information and alerts. Such a twin-tiered method of communication will help in keeping both the consumers and utility providers with real time information at all times. A load control mechanism using relay, remote disconnection and reconnection of supply is built in the system. The feature allows the utilities to control the power distribution during peak hours, overdue payments or abnormal use. The introduction of solar energy is one of the essential innovations in the proposed design. The system also automatically provides the solar energy source whenever the sun is shining so that the energy source does not depend on the grid but rather on the sun to save energy as well as encourage the use of renewable energy sources without necessarily involving human intervention. Fire and gas leakage sensors are needed to improve the reliability and safety of users, as proposed in the system. To avert accidents, the system automatically sends the user alerts in case a hazardous condition occurs through SMS/IoT dashboard and breaks the loading line with the help of the relay.

A. Benefits of the Proposed System

i. Remote monitoring and billing- IoT dashboard allows consumers and utilities to see their real-time usage and GSM based SMS allows them to receive updates on their bills.

ii. Automated Load Control - Relays Remote switching of loads prevents simply overconsuming the load, unauthorized usage of the load, or late payments.

iii. Solar Integration - The system uses renewable solar energy when accessible and switches off to the grid to enhance independence on renewable energy and mitigate carbon emission.

iv. Increased Safety Measures- The fire and gas leakages sensors are added to enhance safety because they can give automatic warnings and disconnect during a safety rollout.

v. Transparency and Accuracy - Removes inaccuracy in the manual reading of meters and gives an accurate and tamper-resistant consumption data.

vi. Easy Interface Control- Indicating the local monitoring of the LCD display and the graphical, real-time statistics of the energy consumption site in the IoT.

vii. Scalable and Cost-Effective: The design can easily be scaled to households, commercial or industrial buildings at very little extra expense.

B. Hardware Required

i. Nodemcu-esp8266 micro controller unit.
ii. Lcd display
iii. GSM modem
iv. Current sensor
v. Relay
vi. Gas sensor
vii. Fire sensor
viii. Solar panel
ix. Connecting wires
x. Soldering kit

C. Software Required:

i. EMBEDDED C
ii. ARDUINO IDE
iii. PHP – MYSQL

4. Simulation Setup

48 hour time scale with each time break of 5 minutes. Individual load items: must have, controllable (AC/heater), and shiftable (washer/ EV charging). Solar PV with inverter cap. Battery storage (5kWh) and charge/discharge capacity and efficiency. Predictive control (EWMA forecast) to anticipate the future shedding of the controllable loads when a prediction of the peak goes above a given threshold. Safety alerts (fire/gas) shutting down automatically after a period of time. Texas: There were also rules on planned remote grid disconnection. Measures of central tendency (simulation-based) The initial radar chart (refer to Appendix 1) indicates the company's financial performance in the initial three years of operation. <|human|> Key summary measures (following the simulation) The first radar chart (see Appendix 1) shows the financial performance of the company during the first three years of operation.

i. Total energy (kWh): 21.044
ii. Solar energy delivered (kWh): 10.464
iii. Grid energy delivered (kWh): 0.422
iv. Battery throughput (kWh): 19.041
v. Fraction from solar: 0.497 (≈49.7%)
vi. Safety events triggered: 1
vii. Controllable load shed time 15 minutes.

4.1 Block Diagram

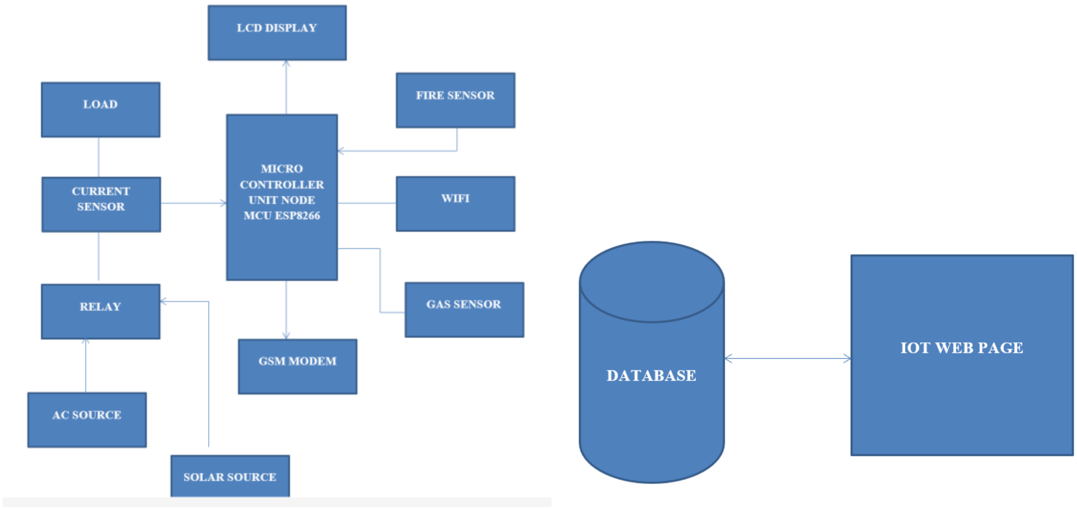

Figure 1: Block Diagram

5. Results and Outputs:

5.1 Results

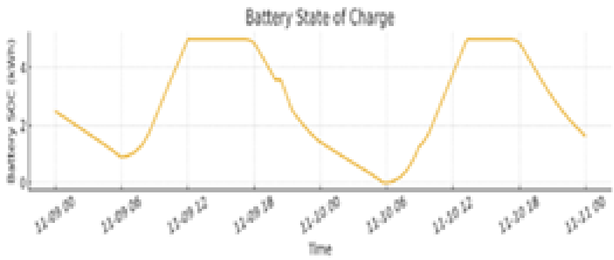

Figure 2: Battery state of charge

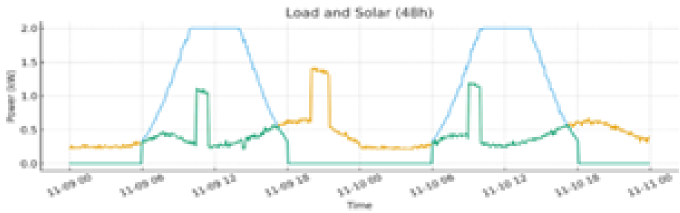

Figure 3: load and solar(48h)

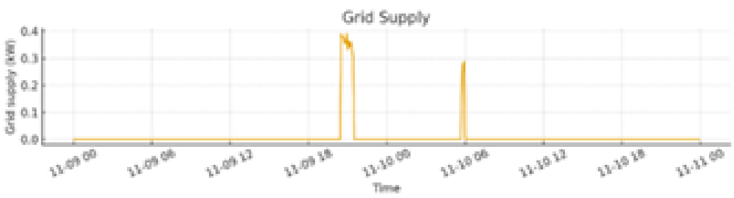

Figure 4: Grid supply

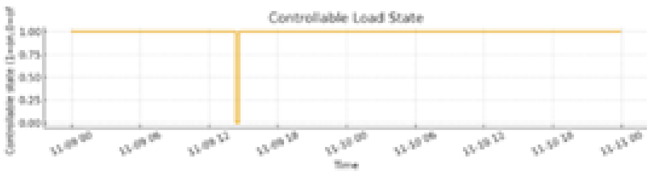

Figure 5: controllable load state

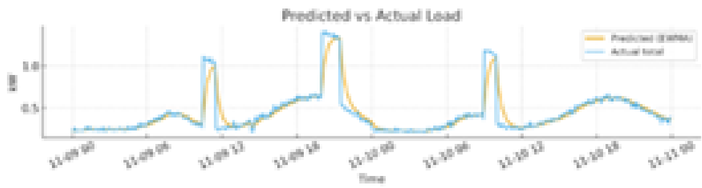

Figure 6: predicted vs actual load

a) Real-Time Data Transmission: The data on consumption was sensorially recorded with a current sensor and shown on a current LCD and an IoT dashboard.

b) Remote Billing and Alerts: The GSM module also sent SMS updates to users concerning energy use, bill and fault detection with high reliability hence eliminating human participation.

c) Solar-Grid Optimization: The system automatically turned on or off the solar and grid power depending on the availability of the power, which was efficient in utilizing the renewable energy.

d) Load Control: The relay mechanism enabled the disconnection/reconnection of loads remotely thus the effective control of the loads in the peak condition or during any payment delays.

e) Safety Response: Fire and gas sensors were integrated to report unsafe situations immediately and interrupt the power to avoid accidents.

f) System Reliability and Scalability: The testing had confirmed stable operation, low data communication latency and easy scalability to larger residential or industrial applications.

i. CSS of full simulation: simulation/data/simulation proper results.csv.

ii. An interactive table previews (first 200 rows), interactive and a summary table (formatted in the run).

iii. Plots: Fixed load, PV and PV available (48 h).Predictive shedding of controllable load state (on/off) is indicated. Battery State of Charge. Grid supply (when used).predicted (EWMA) and actual load.

Measures of central tendency (simulation-based) The initial radar chart (refer to Appendix 1) indicates the company's financial performance in the initial three years of operation.<|human|>Key summary measures (following the simulation) The first radar chart (see Appendix 1) shows the financial performance of the company during the first three years of operation.

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Grid energy delivered (kWh): 0.422

Battery throughput (kWh): 19.041

Fraction from solar: 0.497 (≈49.7%)

Safety events triggered: 1

Controllable load shed time 15 minutes.

Conclusion:

The devised smart energy meter platform has been capable of applying IoT, GSM communication, solar-grid optimization and safety automation to a platform. It removes the negative aspect of traditional energy meters such as the inability to monitor the energy usage in real-time, billing, or intelligent load management. The reliability and efficiency of the system are guaranteed by the fact that the data transmission is made easily between the sensors, web interface, and user devices since the microcontroller is based on the ESP8266. Integration of the solar power greatly diminishes the reliance on the grid and advances the use of renewable sources of energy. The fire and gas leakage sensors help to improve the user safety since automatic load disconnection and immediate alerts in case of a hazard situation occur. The experimental outcomes attest to the fact that the proposed system is accurate, secure, and scalable enough to offer energy management in the residential, commercial, and industrial settings. Therefore, this initiative provides a cost-efficient solution, which is sustainable and helps in achieving the vision of a smart, safe, and energy-efficient power grid of the future.

Future Scope:

- Enabling possibilities to be integrated with Smart Grids:
- This system can be improved to be able to communicate with smart grids to transmit energy distribution in real-time, faults, and demand-side management.
- Algorithms: Mechatron/iq based: Intersection-detecting: Horizon: IoT: IoT19: Cloud: Cloud-based: Monitoring:
- The further editions can be equipped with IoT platforms and cloud databases to provide mass data storage, analytics and monitoring using web or mobile dashboard.
- The predictive and optimization of the AI used to detect loading in flat rates:
- Artificial Intelligence (AI) algorithms can easily be introduced to forecast the patterns of energy consumption and automatically manage the distribution of the loads to optimize their cost.
- Could things like wind, solar, hydroelectric, and bio-energy be recycled?<|human|>Renewable Energy Compatibility:
- The system may be pushed to a solar or wind energy source, where a tracking of renewable additions and optimization of hybrid energy systems occurs.
- Increased Data encryption and security:
- Billing Initiating a blockchain or improved encryption can facilitate secure billing transaction and avoid tampering and energy robbery of data.

- Smart Home integration algorithms: Basic Component, PID controller, Analyzer, setpoint, hysteresis Moving Car: Driving controller, collusion controller, steering controller, brake controller, analytics controller State Transducer: Worsted pose estimator, agile controller, chassis controller, position controller Systems with Optimization Large Fantasy Car: Driving controller, collusion controller, steering controller, brake controller, analytics controller State Transducer: Worsted pose estimator, agile controller, chassis controller, position controller Systems with Optimization Large Fantasy Car:
- The design is open to home automation systems or smart load Control, which enhances energy efficiency and convenience of the user.
- Dynamic Tariff: This feature provides the customer with the ability to enter their contact details for edits and amendments like name and address, billing image choice, payment details, and invoice number editing.<|human|>Automated Billing: This segment of the application allows customer to update their contact information in changing and amending it, such as adding a name and address, selecting an image to use on their bill, adding payment information, and editing invoice numbers.
- The billing system can be more flexible and easy through real-time updates on tariffs and automated mobile billing systems via online payment gateway.
- Predictive Maintaining and Fault Yellow Wall:
- Sensors and machine learning can become part of the future systems so that a lack of proper connections, over loads, or abnormal power usage can be noticed, and there is less downtime and fewer hazards.
- Utility Providers: Utility providers can be scaled up and down.
- The design can be expanded to hundreds of consumers and thousands can be served by remote management of power meters, consumption patterns and infrastructure projects will be planned effectively.
- Government Linkages: Government Smart City Program Fleur-de-lis smart city initiatives:

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STATUS, PROSPECTS AND CHALLENGES OF ORGANIC FARMING IN INDIA

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Abstract:

Practice of organic farming in India is a thousand-year-old process. In past many years Humans was totally depends on organic farming. With the development of Chemistry, a no of fertilizers, pesticide, insecticide and many other chemicals are evolved with time. In old time for many years Indian Agriculture also using organic techniques. The fertilizers, pesticides that are used were obtained from living organism or their dead body. Now a days organic farming process is gaining High interest from the society. As we know that intensive conventional farming can add contamination to food chain. The consumers are in search of safer and good quality food. In India people having indigenous skills may accelerate the growth of organic agriculture. Therefore, organize farming has great impact on the health of a nation like India by ensuring sustainable development.

Keywords: Conventional Farming, Organic Agriculture, Food Safety, Organic Techniques.

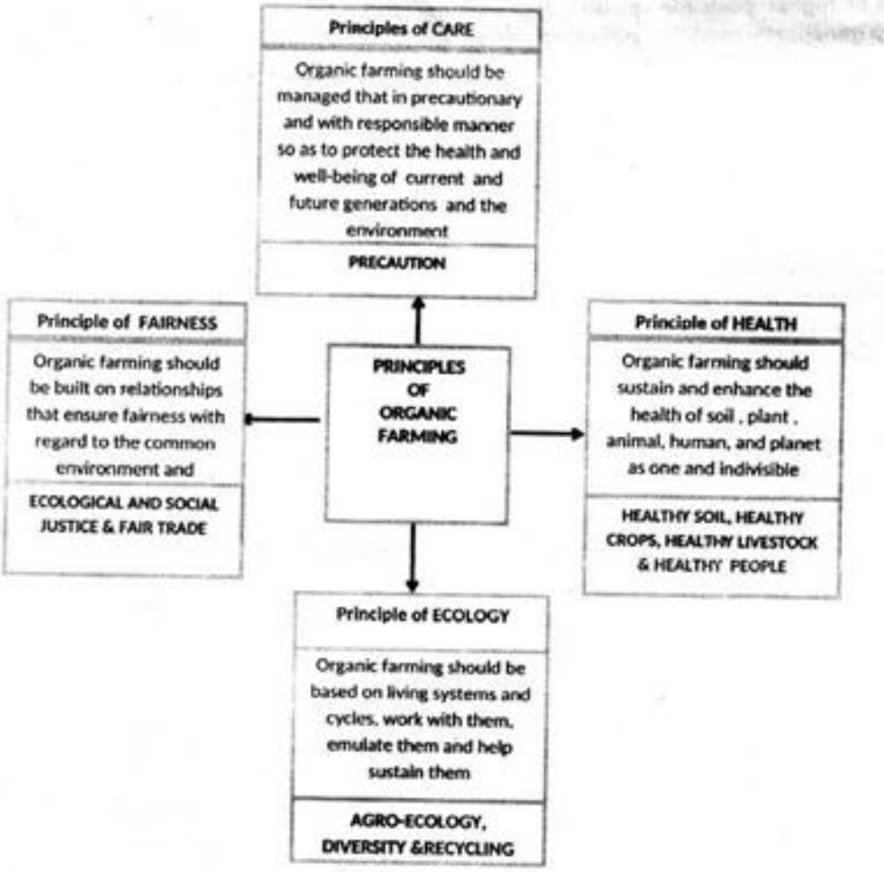
Introduction:

Contamination free and quality food are basic properties attained the attention of common people. Continuous increment in environmental awareness and food contamination with harmful chemicals (e.g., Dioxgin) pathogenic microbes have host the trust to food quality.

In past few years demand for organic food increased tremendously due to their quality and safety. Some research article mentioned that organic produce without using synthetic fertilizers pesticides, weedicides which were used in conventional agriculture processes are discouraged and for this purpose popularity of organic farming is becoming very popular. The area of interest in organic farming is becoming very popular now a days.

Process of Organic Farming:

Best Practices in the field of organic farming shows wide range. This is also required for the new food production system. Four basic principles of organic farming i.e., the principle of health, ecology, fairness and care are suggested by International Federation of Organic Agriculture movements (IFOAM) (Fig.-1). The most important application of natural food production is to improve biological cycles in, to also to manage soil fertility, reduce pollutant in the environment. By Avoiding the application of pesticides and synthetic fertilizers environmental pollution can be controlled. Conservation of genetic diversity in food also have socio-ecological impact of food production and thus it may produce high quality food in sufficient quantity (IFOAM, 1998).



National organic programme developed and implemented by USDA organic food production ACT (OFPA, 1990). In organic farming crops should be cultivated in crop fields without any synthetic pesticides, fertilizers and herbicides for three years before harvesting with enough buffer zone to lower contamination from adjacent farms.

Fertility and nutrient content of soil are managed mainly through farming practices such as crop rotation, using cover crops. Pests, diseases and needs are mainly controlled by using physical and biological control systems by avoiding synthetics pesticides, herbicides.

Discussion:

Advantages of Organic Farming

Nutritional Benefits and Health Safety:

AFSSA-2003 in his report revealed that organically grown foods have higher dry matter as compared to conventionally grown food. Although organic cereals and their products have lesser protein than conventional cereals but they have more quality proteins and better amino acid scores Lysine content in organic wheat. Organically fed cow's muscles contain four times more likolenic acid, which is recommended cardio-protective -3 fatty acid. The milk produced from organic farms contains higher vitamin E and PUFA (Lund, 1991). Organic plants contain significantly more Mg^{2+}, Fe^{2+}, and PO_4^{3-}. These also have more Ca_2+, Na+, K+ as major nutrient and Mn, Iodine, Chromium, Mb, Selenium, Boron, Cu, V, Zn as trace elements (Rembialkowska, 2007).

According to review of Cairon (2010) which was based on french agency for food safety (AFFSA) report, there is more amount of dry matter, minerals and antioxidants such as polyphenols and salicylic acid. There are no residues of pesticides in organic food as compared to conventionally grown foods. The secondary metabolites such as poly phenols, resveratrol and carotenoids have regulatory effects at cellular level and hence found to be protective against certain diseases like cancers, chronic inflammations.

According to a food marketing institute (2008), some organic foods like corn, strawberries and marionberries have 30% more cancer fighting antioxidants.

Rossi *et al.* (2008) in their study shows that organically grown some of the Solanaceae family fruits have more salicylic acid as compare to others. Salicylic acid is an organic aromatic acid having benzene ring. It is found to be anti-inflammatory, anti-stress effects and helps in preventing hardening of arteries. This may cause bowl cancer (Rembial Kowska, 2007; Butler *et al.* 2008).

Food produced by organic farming without using pesticides and sewage sludge they are less contaminated with pesticide residue and pathogenic organisms like Listeria monocystogenes, salmonella sps, E. coli Van Renteroghem et al, 1991, Lung et al, 2011, Warnick et al, 2001)

Therefore, organic food, ensure better nutritional benefits and health safety.

Organic Agriculture and Sustainable Development.

The idea of sustainability in organic farming depends upon the principle of that we must meets the requirements of the present generation without compromising the ability of future generations to their own needs-In sustainable agriculture there is integration of three main objectives – environmental health, economic benefits and socio-economic equity.

Following is the steps in achieving organic farming goals-

1. To improve natural landscape and agroecosystem.
2. overexploitation and pollution of natural resources must be reduced.
3. Reduction in consumption of non-renewable energy resources.
4. Maintenance and improvement of soil health by increasing use of soil by increasing use of soil organic manures.
5. Optimum economic returns with safe, secure and healthy working environment.
6. Application of indigenous knowledge and traditional farming system.

Conventional farming causes continuous degradation of soil fertility by using intensive synthetic fertilizers, pesticides leading to the production loss and increases the cost of production which makes the farming economically unsustainable

Social Sustainability:

It is a process or framework that promotes the wellbeing of members of an organization while supporting the ability of future generations to maintain a healthy community. It can be improved by enabling rural poor to get benefits from agricultural development, giving respect to indigenous knowledge, promoting gender equality in labour , complete participation of rural community to enhance their physical and mental health. Organic farming appears to generate 30% more employment in rural areas and labor achieves higher returns per unit of labour inputs (Pandey and Singh, 2012).

Status of Organic Farming in India.

Organic farming has continued to grow across the world. Since 1985 total area of agricultural land under organic production has been increased steadily over the last three decades (Willer and Lernoud, 2019). Which is the largest growth ever recorded in organic farming. (Willer and lernond 2019). The countries with the largest areas of organic agricultural land recorded in 2017 are given in Fig.2.

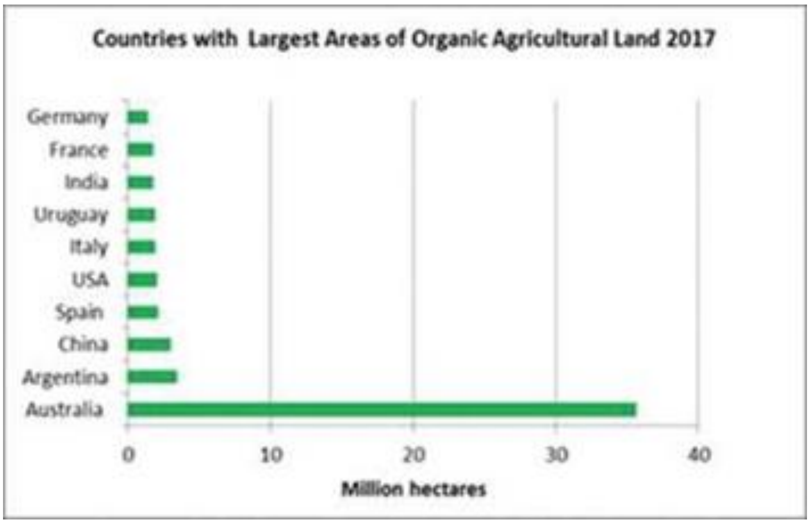


Figure 2: Country-wise areas of organic agriculture land, 2017 (Willer and Lernoud, 2019)

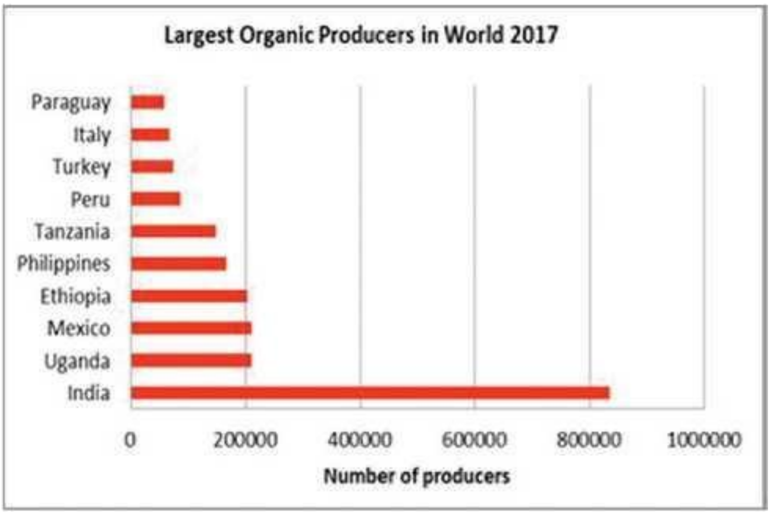


Figure 3: Organic producers by region, 2017 (Willer and Lernoud, 2017

There were several major drawbacks in the growth of organic farming in India which includes –

(a) Lack of awareness
(b) Lack of good marketing policies Shortage of biomass
(c) Inadequate farming Infrastructure
(d) High input cost of farming
(e) In appropriate marketing of organic input
(f) Lack of Financial support
(g) Lack of Financial support
(h) Inability to meet the export demand
(i) Low yield
(j) Lack of quality standard for manure.

Govt. of India, recently has implemented a number of programs and schemes for boosting org. farming in the country Among there the most important are-

i. Paramparagat Krishi Vikas Yojna
ii. Organic Value Chain Development in North eastern Region Scheme
iii. Rastriya krishi Vikas Yojna.
iv. Mission for integrated Dev. Of Horticulture.
v. National programme for organic production.
vi. National Mission for sustainable agriculture (Yadav, 2017).

Paramparagat Krishi Vikas Yojna since 2015-16 and Rastriya Krishi Vikas Yojna are the schemes taken by Govt. of India under BNF policy (Sobhana et al, 2019). According to Kumar (2020), the Union Budgset 20-2021 Rs. 687.5 crore has been allocated for organic farming sector which was 461-36 crore in previous year.

Major states involved in organic agriculture in India are Gujarat, Kerala, Karnataka, U.K., Sikkim, Rajasthan, Maharastra, Tamil Nadu, M.P., H.P (Chandra Shekhar, 2010).

Conclusion:

India is an agriculture-based country with 67% of its population and 55% of manpower depending on farming and related activities. In Current scenario the requirement of healthy life is must. Organic farming is becoming a valuable tool in achieving healthy life goal. As the Population Increasing production of food material also required growth quantitively as well as qualitatively. In future India with its indigenous knowledge, large land area, great man power, suitable climatic condition will definitely become on of the leader in the field of organic farming among the countries of world.

Indian traditional farmers possess a deep insight based on their knowledge, extensive observation, perseverance and practices for maintaining soil fertility, and pest management which are found effective in strengthening organic production and subsequent economic growth in India. The progress in organic agriculture is quite commendable. Currently, India has become the largest organic producer in the globe (Willer and Lernoud, 2017, 2019) and ranked eighth having 1.78 million ha of organic agriculture land in the world in 2017 (Sharma and Goyal, 2000; Adolph and Butterworth, 2002; Willer and Lernoud, 2019).

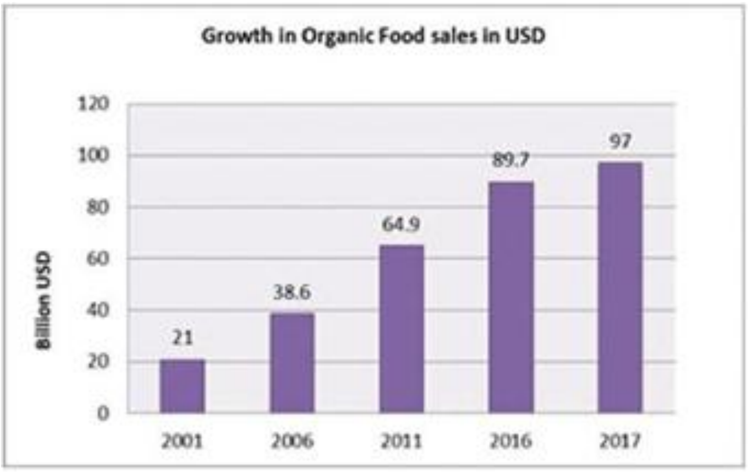


Figure 4: Worldwide growth in Organic Food sales (Willer and Lernoud, 2019)

Various newer technologies have been invented in the field of organic farming such as integration of mycorrhizal fungi and nanobiostimulants (to increase the agricultural productivity in an en- vironmentally friendly manner), mapping cultivation areas more consciously through sensor technology and spatial geodata, 3D printers (to help the country's smallholder), production from side streams and waste along with main commodities, promotion and improvement of sustainable agriculture through innovation in drip irrigation, precision agriculture, and agro-ecological practices.

Conclusions:

Organic farming yields more nutritious and safe food. The popularity of organic food is growing dramatically as consumer seeks the organic foods that are thought to be healthier and safer. Thus, organic food perhaps ensures food safety from farm to plate. The organic farming process is more eco-friendly than conventional farming. Organic farming keeps soil healthy and maintains environment integrity thereby, promoting the health of consumers. Moreover, the organic produce market is now the fastest growing market all over the world including India. Organic agriculture promotes the health of consumers of a nation, the ecological health of a nation, and the economic growth of a nation by income generation holistically. India, at present, is the world's largest organic producers (Willer and Lernoud, 2019) and with this vision, we can conclude that encouraging organic farming in India can build a nutritionally, ecologically, and economically healthy nation in near future.

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A STUDY OF ENVIRONMENTAL INFLUENCES ON FLOW BEHAVIOR IN CD NOZZLES

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Abstract:
Ambient pressure is a critical parameter governing the flow behavior in convergent–divergent (CD) nozzles, as it directly affects the pressure ratio between the nozzle inlet and exit (Singh *et al.,* 2019). This pressure ratio determines the extent of flow expansion and the resulting exit Mach number. When the ambient pressure matches the designed exit pressure, the nozzle operates under ideally expanded conditions, achieving maximum efficiency and optimal thrust Sokolov and Chernyshov, 2018). In practical applications, CD nozzles often operate under off-design conditions, leading to under-expanded or over-expanded flows. Under-expanded flow occurs when the exit pressure is higher than the ambient pressure, causing the jet to continue expanding outside the nozzle through expansion fans (Tsutsumi *et al.,* 2006). Conversely, over-expanded flow arises when the exit pressure is lower than the ambient pressure, resulting in compression of the flow and the formation of shock waves. Shock formation may occur either inside the nozzle or in the external jet, depending on the degree of pressure mismatch (Johnson and Papamoschou, (2010). In severe over-expanded conditions, strong adverse pressure gradients can induce boundary layer separation within the divergent section. Such flow separation leads to unsteady behavior, loss of thrust, increased side loads, and potential structural issues, making ambient pressure effects a key consideration in nozzle analysis and design (Chen *et al.,* 1994).

Keywords: Convergent–Divergent Nozzle, Environmental Effects, Compressible Flow, Shock Waves, Nozzle Performance.

1. Introduction:

Convergent-divergent (CD) nozzles are a basic element in high-speed aerodynamic, and propulsion systems, both in the aerospace and rocket domains where efficient acceleration of compressible fluids are needed (Khan *et al.,* 2021). CD nozzles also allow subsonic flow to be stepped up to sonic in the throat and then be extended up to supersonic speeds in the divergent part, both necessary to achieve high thrust and the maximum energy conversion (Munday *et al.,* 2011). It is important to know the behavior of flow in CD nozzles since compressible flow has complex behaviour that include choking, shock wave, expansion fans and flow separation. These effects have a great impact on the mass flow rate, thrust generation and the general nozzle efficiency, particularly when operating in conditions of high speed (Hunter, 2004). The environmental conditions are very important in the determination of nozzle performance.

The changes in ambient pressure, temperature, and atmospheric density have a direct influence on pressure ratios across the nozzle and result in the change of flow regimes, including under-expanded or over-expanded flow (He et al.,2015). Such environmental effects may result in shock development and unsteady flow characteristics, which affects the performance and structural integrity (Matos *et al.,* 2024). This chapter is motivated by the intention to experimentally investigate the effect of environmental parameters on the flow behavior in CD nozzles in a more systematic way (Aabid, A., and Khan, S. A. 2021). The coverage encompasses theoretical background, experimental studies and mathematical studies. The chapter has been structured in such a way that it provides the basic concepts, then the environmental impacts, analysis and finally the design implications (Michener, 1997).

2. Fundamentals of Flow in CD Nozzles

A convergent-divergent (CD) nozzle is a convergent, then a throbore, and divergent nozzle that is designed to achieve a high velocity of an accelerating compressible fluid effectively (Khan *et al.,* 2021). Subsonic flow gains velocity in the convergent section which narrows its cross-sectional area to the sonic level of Mach number (equal to unity) at the throat when its pressure ratios are suitably aligned (Huang,2018). The diverging part, which starts above the throat, allows the flow to accelerate further to supersonic speeds by sideways expansion, which is controlled (Dussauge and Gaviglio, 1987). A CD nozzle can be operated under a subsonic regime, sonic regime, or supersonic regime depending on the stagnation conditions in the inlet and the ambient pressure (Vadivelu *et al.,* 2022).

The pressure ratio across the nozzle is too high beyond a critical value the flow chokes and the mass flow rate becomes a constant, not dependent on any changes in the downstream pressure (Abdelhafez and Gupta, 2010). This is a choked flow of compressible nozzle. The operation of a CD nozzle involves shock waves and expansion processes, especially in the off-design conditions (Lv *et al.,* 2017). Expanded flows can generate either normal or oblique shock waves and under-expanded flows can generate expansion fans below nozzle exit (Yu, 2020). These effects have a great impact on performance and stability of flows. The most important key performance parameters of CD nozzles are thrust, mass flow rate, exit velocity, and efficiency (Vadivelu *et al.,* 2022). The correct knowledge of these basics is fundamental to the analysis of the environmental impact and the optimization of nozzles construction (Boretti and Huang ,2024).

3. Environmental Parameters Affecting CD Nozzle Flow

The environmental conditions around a convergent-divergent (CD) nozzle have a strong effect on the flow behavior of the nozzle, and the pressure and thermal limits of the nozzle exit depend on these factors (Raju *et al.,* 2025). Among them, the ambient pressure has the most significant role because it dictates the pressure ratio across the nozzle directly and affects the extent of the flow expansion (Hamzehloo and Aleiferis, 2016). Fluctuations in the ambient pressure may produce under-expanded or over-expanded flow states, and shock generation, separation of the flow and performance of the nozzle (Khan et al.,2022). Nozzle flow is also influenced by ambient temperature through the change in the properties of gas density, speed of sound and viscosity (Ma et al.,2022).

Temperature variations have an effect on Mach number distribution, mass flow rate and thrust generation, especially at high altitude or extreme thermal conditions (Zhou et al.,2025). A combination of effects of decreased atmospheric pressure and density is introduced by altitude, which has a considerable effect on the operation of the CD nozzle in both aerospace and propulsion settings (Wang et al.,2023). The lower density environments alter expansion properties and may increase or reduce performance by the nozzle design and operational conditions (Gradl and Protz,2020). Under some circumstances, particularly at high pressures and temperatures, humidity and real-gas effects may be important to the thermodynamic properties, despite being neglected in simplified analyses (Beattie, 1949). Also, external disturbances like atmospheric turbulence, variations of the environment can also cause unsteady flow behaviour, which can influence stability and efficiency (Lilly, 1960).

4. Influence of Ambient Pressure on Flow Behavior

One of the essential parameters that control the flow behavior of convergent-divergent (CD) nozzles through their direct influence on the pressure ratio of the nozzle inlet and exit is ambient pressure (Singh *et al.,* 2019). This ratio of pressure defines the amount of flow expansion and the exit Mach number. At the point at which the ambient pressure equals the designed exit pressure, the nozzle works in ideally expanded conditions, with the highest efficiency and ideal thrust Sokolov and Chernyshov,2018). In practice, the nozzles used in CDs tend to be used under off-design conditions causing under-expanded or over-expanded flows. Under-expanded flow is the flow that exists when the pressure at the exit is greater than the pressure in the ambient which makes the jet to expand further beyond the nozzle with the help of expansion fans (Tsutsumi *et al.,* 2006). On the other hand, over-expanded flow occurs where the exit pressure is below the ambient pressure and this causes the compression of the flow and this leads to the emergence of shock waves. Depending on the extent of mismatch in pressure, shock formation can either be in the nozzle or in the external jet (Johnson and Papamoschou, (2010). This separation in flow causes unsteady behavior, thrust loss, enhancement of side loads and possible structural problems, so the effects of ambient pressure are of great importance to nozzle analysis and design (Chen *et al.,* 1994).

5. Temperature Effects on CD Nozzle Performance

Another impact of ambient temperature on convergentdivergent (CD) nozzles is their effect on the performance of the nozzles in terms of flow kinematics and thermodynamic characteristics of the working fluid (Olson and Lele, 2013). Change in ambient temperature changes the local speed of sound that has a direct effect on Mach number distribution and exit velocity of the flow. Increased ambient temperatures make sound travel faster resulting in lower Mach numbers whereas decreased ambient temperatures do the reverse (Lau, 1981). Alteration of ambient temperature also affects the density of gases and stagnation characteristics leading to the change in mass flow rate and thrust generation.

When ambient temperatures are low, density increases, and this could improve the rate of mass flow and thrust, and in some operating conditions, when temperatures are high, the total nozzle performance is diminished (Ye *et al.,* 2017). The thermal influence on gas properties including specific heat ratio, viscosity, and thermal conductivity is of greater concern in the high-temperature conditions (McLaughlin, 1964). Such differences may have an impact on boundary layer behavior, stability of flows, and strength of shocks. In high-altitude and high-temperature applications, there is a strong need to consider correctly the effects of temperature on the design and operation of nozzles, performance, and safe operation in aerospace and propulsion systems (Bian *et al.,* 2025).

6. Altitude and Atmospheric Effects

The effect of altitude on convergent divergent (CD) nozzles flow behavior and performance is severe because the atmospheric condition is constantly changing with the height (Xin *et al.,* 2025). With an increase in altitude, ambient pressure, temperature, and density of the air drop, which causes pronounced variations in pressure ratio across the nozzle and the following expansion peculiarities of the flow (Wiśniewsk *et al.,* 2022). CD nozzles are also more prone to flow expansion in low-pressure conditions and usually work near ideally expanded or under-expanded conditions (Aabid and Khan, 2021). Lower ambient pressure can improve the exit velocity and thrust efficiency, but also increase shock structures during off-design situations (Gramola *et al.,* 2020). The effects are also significantly relevant in high-altitude flight regimes and space propulsion systems, where ambient pressure is close to near-vacuum. In the case of rocket propulsion, a more desirable altitude-compensating nozzle design is typically better because it is more effective at high altitudes because back pressure is lower and nozzle performance is typically increased. The difference between ground-level and high-altitude operation demonstrates the need to consider the changing atmospheric conditions: nozzles designed to run well at sea-level will be prey to flow separation and efficiency loss at low altitude, whereas nozzles designed to run well at high altitude will be inefficient at low altitude.

7. Flow Instabilities and Environmental Interactions

Hydraulic instabilities in convergent-divergent (CD) nozzles usually occur with the interactions between internal flow structures and external environmental factors (Balabel *et al.,* 2011). When there is a change in ambient pressure and temperature, unsteady shock motion (so-called shock oscillations) can take place and have a considerable influence on flow stability and the work performance of nozzles (Wong, 2006). Such vibrations are normally linked to non-design operating conditions and the vibrations may be subjected to varying loads of pressure in the nozzle. The flow separation in the divergent section can also be caused by unfavourable pressure gradients caused by environmental changes (Na and Moin, 1998). This separation is usually not stable and results in uneven flow distributions, lateral forces, as well as a decrease in performance.

Those effects are critical especially in transient operating conditions like start-up, shut-down, or sudden changes in altitude (Angerer *et al.,* 2017). Flow behavior may also be further affected by acoustical interactions between the exhaust jet and the surrounding environment (Troutt and McLaughlin, 1982). Shock structures and turbulent mixing can produce pressure waves which can couple with the nozzle structure, enhancing unsteady processes (Johnson and Papamoschou, 2010). The cumulative effect of these instabilities can have significant structural and performance implications, such as more vibration, material fatigue, noise production, and lower operational reliability, providing a reason why such nozzle designs and analyses should be carefully considered with respect to the environment (Naqash and Alam, 2025).

8. Experimental and Numerical Studies

Both experimental and numerical studies are crucial to the explanation of the intricate flow dynamics in convergent–divergent (CD) nozzles in different environment conditions (Nair *et al.,* 2020). Hydraulic tools like pressure transducers, schlieren and shadowgraph, particle image velocimetry (PIV) and hot-wire anemometry are some of the common experimental methods that are used to observe shock structures, flow separation and velocity in and outside the nozzle (Zhang, 2000). Controlled studies of how CD nozzles perform under a variety of ambient pressures and temperatures can be conducted with the help of wind tunnels and specialized test rigs that allow to simulate different altitude and environmental conditions (Rose *et al.,* 2015). These experiments offer good understanding of the behaviour of the real flow, such as unsteady flows and interactions with the environment which are hard to predict in a deterministic manner (Hu *et al.,* 2025). The computational fluid dynamics (CFD) has emerged as an essential instrument in the analysis of the flow through a nozzle where one can visualize the field of flow and conduct a parametric study in varying operating conditions. Numerical simulations are useful in forecasting the behavior of shocks, turbulence and measures of performance. To achieve success in the application of the CFD results, it is necessary to compare the obtained results with experimental data, which would guarantee their accuracy and reliability, and allow the application of the numerical models with confidence when designing and optimizing the CD nozzle (Rafiee and Rahimi, 2013).

9. Design Implications and Engineering Applications

Nozzle design and use have serious implications on environmental effects of flow behavior on convergent-divergent (CD) nozzles. Good design solutions should be able to take into consideration the difference in ambient pressure, temperature, and altitude in order to guarantee the ability to provide stable and efficient operation within a large set of operating conditions. This involves optimization of nozzle geometry to reduce the separation of flow, shock losses and unsteady behavior in off-design conditions. Concepts that mitigate the loss in performance due to variations in environmental conditions have been devised, including dual bell nozzle, aerospike nozzles and variable geometry nozzles. This allows these designs to be more efficient as the expansion characteristics automatically adjust to the atmosphere around. In aerospace propulsion systems such as jet engines, rocket motors, space launch vehicles, CD nozzles are common, and environmental effects are overridingly high. Even with improved design techniques, the issues have existed in the correct forecast of the unsteady flow behavior, material performance at extreme conditions, and merging with propulsion systems. The next generation of design will be based on the advanced materials, intelligent control mechanisms, and high-fidelity simulations that will be used to improve nozzle adaptability, reliability, and performance.

10. Case Studies

The case studies also give a realistic understanding of how convergent-divergent (CD) nozzles work in the real world given different environmental conditions (Nejaamtheen *et al.,* 2025). The aerospace and propulsion examples show the effect of ambient pressure, temperature, and altitude on flow behavior and performance in general of the nozzles (Bruccoleri *et al.,* 2012). These are real world situations that assist in closing the gap between theoretical analysis and actual application. Comparisons of performance under varying operating conditions, including high-altitude or near-vacuum environments versus sea-level environments, reveal that environmental changes have a significant effect on thrust efficiency, shock formation, and flow stability (Lee *et al.,* 2020).

These comparisons display the drawback of fixed-geometry nozzles under other than their design conditions (Chen *et al.,* 2017). The things that have been learnt during these real-life applications highlight the significance of designing and testing to be environment-conscious. The information provided by the operational data can be used to enhance better nozzle geometries, adaptive ideas, and predictive models and eventually lead to enhanced reliable and efficient nozzle operation across various engineering applications (Zhao *et al.,* 2025.)

11. Future Research Directions

Future studies on convergent divergent (CD) nozzles will focus on the issues of environmental differences and changing propulsion demands. Innovative materials and intelligent nozzle designs are under development to increase thermal resistance, decrease weight and make the geometries adaptive to respond dynamically to prevailing ambient conditions. This kind of innovation can enhance efficiency, reliability and flexibility of operation. The enhanced prediction of nozzle performance in extreme conditions will become possible due to better modeling of actual-gas effects, the thermodynamics of high temperature, and environmental effects.

Through their use in combination with high-fidelity computational fluid dynamics (CFD) and multi-physics simulations, they can be used to capture the unsteady flow phenomena, shock interactions, and flow separation with increased accuracy. New experimental methods such as state-of-the-art optical diagnostics, high-speed imaging, and non-intrusive measuring instruments will also give a new validation and refinement to theoretical and numerical predictions. There is also the consideration of environmental sustainability, which include minimizing emissions and maximizing fuel efficiency, which is also being considered in the design of nozzles. The future of innovation in these fields will be through further research to enable CD nozzles to be efficient and sustainable to the aerospace and propulsion needs in the future.

Conclusion:

The chapter has discussed the important role of environmental conditions in the flow behavior and performance of convergent divergent (CD) nozzles. Among such findings, it has been determined that the change in the ambient pressure, temperature, altitude, and atmospheric density have critical impact on flow regimes, shock development, mass flow rate and thrust development. Unsteady phenomena, flow separation, and under-expanded or over-expanded flows may occur in off-design conditions and it is important to consider the effects on the environment in the analysis of nozzles.

The results of experimental studies and computational simulations offer a complementary solution, allowing to predict and verify the performance of nozzles under a variety of operating conditions. Such results highlight the importance of changing and altitude-compensating nozzle shapes, novel materials and modeling technologies in order to retain the efficiency and dependability in practice. All in all, the design of the nozzle in the CD must be learnt and the environment factors considered to maximize the performance of the nozzle, ensure the structural integrity and improve the propulsion technology. With these considerations, engineers are able to come up with nozzles that can operate effectively at various atmospheric and high altitude conditions.

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EVOLUTION OF BIANCHI TYPE III ANISOTROPIC UNIVERSE WITH AN AFFINE EQUATION OF STATE

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Abstract:
This chapter investigates the Evolution of Bianchi Type III Anisotropic Universe with the Affine Equation of State $p = \alpha\rho - \beta$. The Einstein field equations corresponding to the Bianchi Type-III metric are derived and solved, with an Affine Equation of State Parameter. The model gives an anisotropic universe undergoing accelerated expansion.

Keywords: Bianchi Type III, General Relativity, Affine EoS, Accelerated Expansion

1. Introduction:

The Bianchi Type-III cosmological model has been extensively explored due to its anisotropic nature, which provides a rich framework for studying the universe's evolution under various theoretical constructs. Research has examined models with linear equations of state (Adhav *et al.,* 2014), dark energy scenarios (Mishra *et al.,* 2015; Kumar and Satyannarayana, 2015; Sahu *et al.,* 2016; Tiwari *et al.,* 2018; Deniel *et al.,* 2020; Sharma *et al.,* 2020; Mahanta and Das, 2021; Nerkar and Dawande, 2022), and electromagnetic fields with cosmic strings (Deo *et al.,* 2015). String cosmological models have been investigated with various matter sources, including strange quark matter attached to string clouds (Sahoo and Mishra, 2015; Chirde and Kadam, 2016), bulk viscous fluids (Soni and Shrimali, 2015; Sahoo *et al.,* 2017; Sen *et al.,* 2021; Jnana *et al.,* 2024), and modified string configurations (Tiwari *et al.,* 2019; Chhajad *et al.,* 2021). Tilted configurations have been explored in different geometric frameworks (Sahu *et al.,* 2015; Sahu *et al.,* 2016), while wet dark fluid scenarios have been studied (Sahu *et al.,* 2016; Tade *et al.,* 2016). Modified gravity theories have received significant attention, including f(R) gravity (Banik *et al.,* 2017; Banik *et al.,* 2018; Shabbir *et al.,* 2019), f(R,t) and f(R,T) theories (Tiwari *et al.,* 2019; Mishra and Sharma, 2024), f(T) gravity (Nerkar and Dawande, 2022), and f(G) gravity (Basumatary and Dewri, 2023). Holographic dark energy models have been examined (Srivastava *et al.,* 2019; Sharma *et al.,* 2020; Mahanta and Das, 2021), along with investigations in Brans-Dicke theory (Chirde and Kadam, 2016; Gaidhane *et al.,* 2024). These investigations highlighted above for the Bianchi Type-III space-time, are is the motivation behind the study of this chapter.

2. Metric and field equations

The Bianchi Type-III space-time can be written as

$$ds^2 = dt^2 - A(t)^2 dx^2 - B(t)^2 e^{-2mx} dy^2 - C(t)^2 dz^2 \tag{2.1}$$

where $A(t), B(t)$ and $C(t)$ are functions of cosmic time t only, and $m \neq 0$ is a constant.

The energy-momentum tensor is given by

$$T_v^u = diag[T_4^4, T_1^1, T_2^2, T_3^3] = diag[\rho, -p, -p, -p] \tag{2.2}$$

where ρ is the energy density of the fluid and p is its pressure.

We assume an affine equation of state [Singh A. (2023)] as

$$p = \alpha\rho - \beta \tag{2.3}$$

where α and β are constant.

The Einstein field equations, in natural limits ($8\pi G = 1$ and $c = 1$), are

$$G_{\mu v} = R_{\mu v} - \frac{1}{2} R g_{\mu v} = -T_{\mu v} \tag{2.4}$$

where $g_{\mu v} u^{\mu} u^{v} = 1$; $u^{\mu} = (1,0,0,0)$ is the four-velocity vector; $R_{\mu v}$ is the Ricci tensor; R is the Ricci scalar and $T_{\mu v}$ is the energy-momentum tensor.

Einstein's field equations (2.4) for metric (2.1), with the help of equations (2.2) and (2.3) can be written as

$$\frac{\dot{A}\dot{B}}{AB} + \frac{\dot{A}\dot{C}}{AC} + \frac{\dot{B}\dot{C}}{BC} - \frac{m^2}{A^2} = \rho \tag{2.5}$$

$$\frac{\ddot{B}}{B} + \frac{\ddot{C}}{C} + \frac{\dot{B}\dot{C}}{BC} = -(\alpha\rho - \beta) \tag{2.6}$$

$$\frac{\ddot{A}}{A} + \frac{\ddot{C}}{C} + \frac{\dot{A}\dot{C}}{AC} = -(\alpha\rho - \beta) \tag{2.7}$$

$$\frac{\ddot{A}}{A} + \frac{\ddot{B}}{B} + \frac{\dot{A}\dot{B}}{AB} - \frac{m^2}{A^2} = -(\alpha\rho - \beta) \tag{2.8}$$

$$m\left(\frac{\dot{A}}{A} - \frac{\dot{B}}{B}\right) = 0 \tag{2.9}$$

where dot (.) denotes the derivative with respect to t.

Integrating equation (2.9) we obtain

$$B = c_1 A \tag{2.10}$$

Where $c_1 = 1$ is the constant of integration.

Using equation (2.10) in equations (2.5)-(2.8), the field equations reduce to

$$2\frac{\dot{A}\dot{C}}{AC} + \left(\frac{\dot{A}}{A}\right)^2 - \frac{m^2}{A^2} = \rho \tag{2.11}$$

$$\frac{\ddot{A}}{A} + \frac{\ddot{C}}{C} + \frac{\dot{A}\dot{C}}{AC} = -(\alpha\rho - \beta) \tag{2.12}$$

$$2\frac{\ddot{A}}{A} + \left(\frac{\dot{A}}{A}\right)^2 - \frac{m^2}{A^2} = -(\alpha\rho - \beta) \tag{2.13}$$

3. Solution of the Field Equations

The field equations (2.11) -(2.13) are nonlinear differential equations. In order to get a deterministic solution, we consider the physical condition that the Shear scalar σ is proportional to scalar expansion θ, which leads to

$$A = C^s \tag{3.1}$$

where $s \neq 1$ is an arbitrary constant.

Let us suppose the scale factor [Mishra et al. (2017)] as

$$a(t) = t^n e^{mt} \tag{3.2}$$

The spatial volume (V) is given by

$$V = ABC \tag{3.3}$$

Thus,

$$C = (t^n e^{mt})^{\frac{3}{2s+1}} \tag{3.4}$$

Also,

$$A = C^s = (t^n e^{mt})^{\frac{3s}{2s+1}} \tag{3.5}$$

Hence,

$$A = B = (t^n e^{mt})^{\frac{3s}{2s+1}} \tag{3.6}$$

The component of the Hubble parameter H_x, H_y and H_z are given by

$$H_x = H_y = \frac{\dot{A}}{A} = \frac{3s}{2s+1}\left(m + \frac{n}{t}\right), H_z = \frac{\dot{C}}{C} = \frac{3}{2s+1}\left(m + \frac{n}{t}\right) \tag{3.7}$$

The Generalized mean Hubble parameter H is found to be

$$H = \frac{1}{3}\frac{\dot{V}}{V} = \frac{1}{3}\left(2\frac{\dot{A}}{A} + \frac{\dot{B}}{B}\right) = m + \frac{n}{t} \tag{3.8}$$

The expansion scalar θ is found to be

$$\theta = 3H = 3\left(m + \frac{n}{t}\right) \tag{3.9}$$

The deceleration parameter q is found to be

$$q = \frac{d}{dt}\left(\frac{1}{H}\right) - 1 = \frac{-\frac{n(n-1)}{t^2} - \frac{2mn}{t} - m^2}{\left(m + \frac{n}{t}\right)^2} \tag{3.10}$$

The anisotropic parameter of the expansion (Δ) is found to be

$$\Delta = \frac{1}{3}\sum_{i=1}^{3}\left(\frac{H_i - H}{H}\right)^2 = 2\left(\frac{s-1}{2s+1}\right)^2 \tag{3.11}$$

where $H_i (i = 1,2,3)$ directional Hubble parameters in the direction of x, y and z axes respectively.

The Shear scalar σ^2 is found to be

$$\sigma^2 = \frac{3}{2}\Delta H^2 = 3\frac{(s-1)^2\left(m + \frac{n}{t}\right)^2}{(2s+1)^2} \tag{3.12}$$

Using equations (3.4) and (3.6) in (2.11), we get the energy density as

$$\rho = \left[\frac{3}{2s+1}\left(m+\frac{n}{t}\right)\right]^2 [2s+s^2] - \frac{m^2}{(t^n e^{mt})^{\frac{6s}{2s+1}}} \tag{3.13}$$

From (2.3) and (3.13), we get pressure as

$$p = \alpha\left(\left[\frac{3}{2s+1}\left(m+\frac{n}{t}\right)\right]^2 [2s+s^2] - \frac{m^2}{(t^n e^{mt})^{\frac{6s}{2s+1}}}\right) - \beta. \tag{3.14}$$

Using equations (3.9) and (3.12), we get the rotation tensor as

$$\frac{\sigma^2}{\theta} = \frac{(s-1)^2\left(m+\frac{n}{t}\right)}{(2s+1)^2} \tag{3.15}$$

Using equations (3.12) and (3.13), we get

$$\frac{\sigma^2}{\rho} = \frac{\frac{(s-1)^2\left(m+\frac{n}{t}\right)^2}{(2s+1)^2}}{3\left[\frac{\left(m+\frac{n}{t}\right)}{2s+1}\right]^2 (2s+s^2) - \frac{m^2}{(t^n e^{mt})^{\frac{6s}{2s+1}}}} \tag{3.16}$$

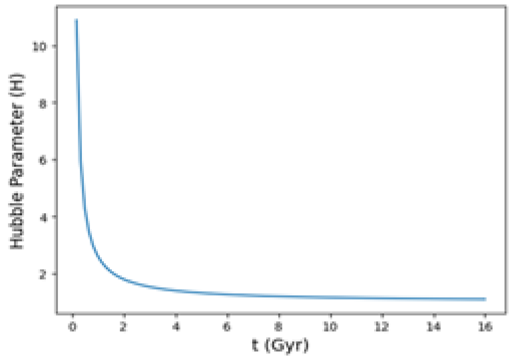

Figure 3.1: Evolution of H vs. t

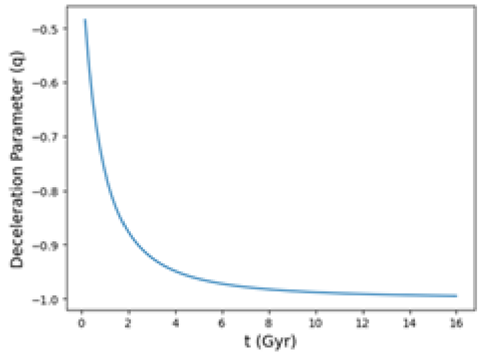

Figure 3.2: Evolution of q vs. t

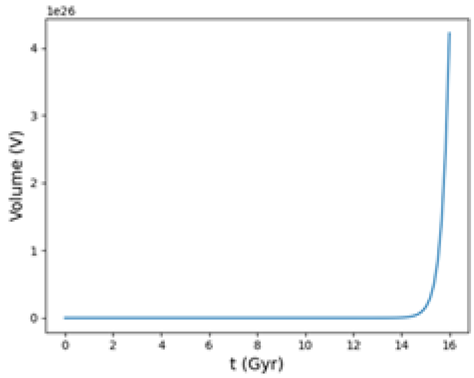

Figure 3.3: Evolution of V vs. t

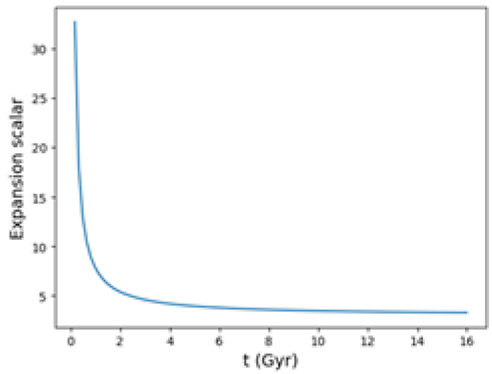

Figure 3.4: Evolution of θ vs. t

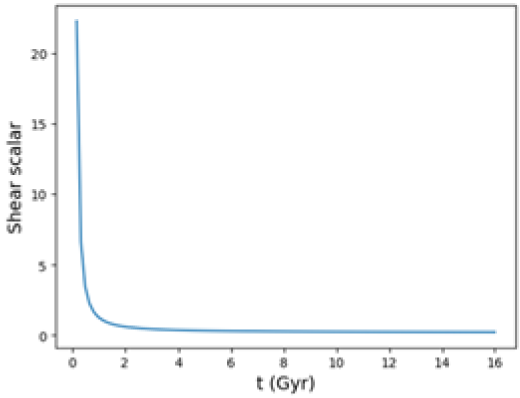

Figure 3.5: Evolution of σ^2 vs. t

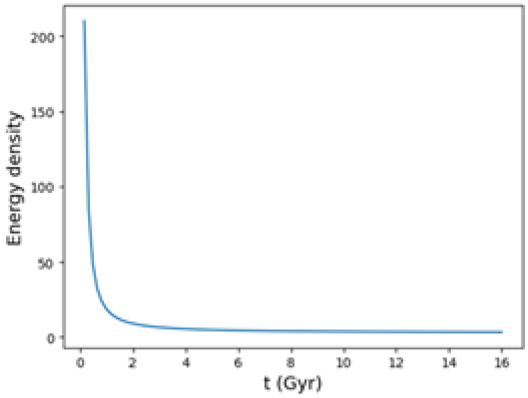

Figure 3.6: Evolution of ρ vs. t

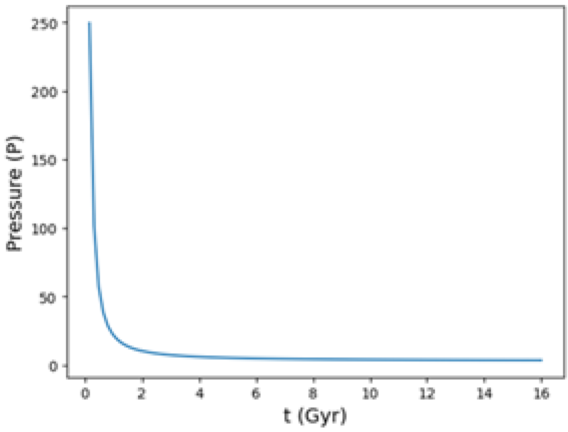

Figure 3.7: Evolution of p vs. t

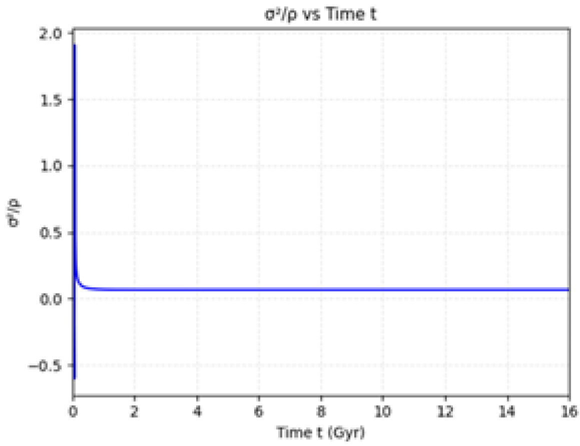

Figure 3.8: Evolution of $\frac{\sigma^2}{p}$ vs. t

Conclusion:

This chapter discusses the dynamics of an anisotropic Bianchi Type-III Cosmological Model with an affine equation of state. The hybrid scale factor $a(t) = t^n e^{mt}$ is used to determine solutions of the field equations. Figures for the various dynamical parameters are presented for $m = 1, n = 1.6, \alpha = 1{,}19,\ \beta = 0.563$ and $s = 0.5$ values. The spatial volume of the model grows as time rises. The Hubble Parameter H decreases over time. The Scalar expansion θ also decrease with respect to time. The energy density ρ and pressure p also decrease over time. Deceleration parameter is in the range $-1 \leq q < 0$. These shows expansion with acceleration of the universe. Analysis of cosmological parameters reveals a unified and physically consistent picture of cosmic evolution: (i)The universe begins in an unstable quantum regime with extreme fluctuations (t < 0.1 Gyr), (ii) A smooth transition occurs from quantum to classical behavior (0.1-1 Gyr), with damping of initial perturbations (iii) Late-time evolution (t > 1 Gyr) demonstrates convergence to stable asymptotic values consistent with observed cosmology, (iv) The model successfully describes the full cosmic history from early instabilities through phase transitions to stable late-time configuration. The unified evolution validates the cosmological model and demonstrates its ability to describe both early-universe quantum effects and late-time accelerated expansion behavior in a single consistent framework.

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