

**ARTIFICIAL
INTELLIGENCE:
MULTIDISCIPLINARY
STANCE AND
APPLICATIONS**

ARTIFICIAL INTELLIGENCE: MULTIDISCIPLINARY STANCE AND APPLICATIONS

Edited by

Dr. Aanchal Arora

Dr. Khushdip Kaur

Dr. Isha Dudeja

VYOM HANS PUBLICATIONS

© 2026 Editors (**Dr. Aanchal Arora, Dr. Khushdip Kaur, & Dr. Isha Dudeja**)

Date of Publications: 24/06/2026

ISBN (E): 978-81-686211-3-8

ISBN (P): 978-81-686211-2-1

Typesetting: LaTeX

Published By-

Imprint: Vyom Hans Publications

Vyom Hans Vision

967/EH1, Industrial Area, DeraBassi,

SAS Nagar (Mohali), PIN-140507, Punjab, India.

E-Mail: sushil.kumar@vyomhansjournals.com

Website: <https://press.vyomhansjournals.com>

Mob: +91 9781711925

Disclaimer:

The authors, editors, and publisher of this volume do not provide medical or professional advice, nor do they endorse the application of any specific methods or techniques. The content is presented solely for academic, educational, and research purposes. Readers are encouraged to exercise scholarly judgment and consult appropriate experts where necessary. The authors, editors, and publisher shall not be held liable for any consequences arising from the use or interpretation of the material presented in this work.

This edited volume comprises contributions from multiple authors. Responsibility for the accuracy, originality, and integrity of each chapter rests solely with the respective contributors. The views and opinions expressed are those of the individual authors and do not necessarily reflect those of the editors or publisher.

Some contributors may have utilized artificial intelligence (AI) tools to support aspects of writing, editing, or data processing. Such use remains the responsibility of the respective authors, who have ensured appropriate verification, validation, and scholarly oversight of all content. The editors and publisher do not assume responsibility for the use of such tools but expect adherence to academic standards of integrity and transparency.

The publisher affirms that the content of this volume does not knowingly infringe upon any existing copyrights or intellectual property rights. If any source has been inadvertently omitted or improperly attributed, the publisher should be notified in writing so that appropriate corrective action may be taken.

Acknowledgement

The Editors sincerely express their gratitude to all contributors whose dedication and scholarly efforts made this publication possible. We deeply appreciate the authors for their valuable chapters, intellectual insights, timely submissions and cooperation throughout the grounding of this book. Their scholastic contributions have enriched the quality and diversity of this book.

We extend our heartfelt thanks to the academic experts for their insightful comments, constructive suggestions; professional guidance and continuous engagement with emerging technologies inspire meaningful academic discourse and innovation.

The Editors also acknowledge the continuous support, patience and assistance provided by the publishing team in bringing this work to completion with efficiency and professionalism.

Finally, we gratefully recognize the encouragement and support received from our institution, colleagues and family members throughout this endeavor.

Editors:

Dr. Aanchal Arora^a Dr. Khushdip Kaur^b Dr. Isha Dudeja^c

^aAssistant Professor, Department of Chemistry, Khalsa College for Women, Civil Lines, Ludhiana, arora.aanchal511@gmail.com

^bAssociate Professor, Department of Commerce, Khalsa College for Women, Civil Lines, Ludhiana, khushdip1170@gmail.com

^cAssistant Professor, Department of Chemistry, Khalsa College for Women, Civil Lines, Ludhiana, ishadudeja275@gmail.com

Foreword

The book “Artificial Intelligence: Multidisciplinary Stance and Applications” is a collective scholarly effort that brings together valuable insights from academicians, researchers and practitioners belonging to diverse disciplines. The volume reflects the rapidly expanding role of Artificial Intelligence (AI) in transforming not only scientific and technological domains but also the humanities, commerce, management, governance, and social sciences.

Artificial Intelligence has emerged as one of the most revolutionary developments of the twenty-first century. Its influence extends far beyond automation and computational efficiency, shaping the way societies function, businesses operate, scientific discoveries are made, and human creativity evolves. The chapters included in this volume explore a broad spectrum of themes that demonstrate the multidimensional applications of AI. As AI continues to disrupt traditional business models and redefine operational strategies across sectors, this book brings together diverse perspectives that critically examine its potential, implications, and future trajectory. AI is expected to bring attractive and profitable opportunities to various industries of India. But its effective use and its contribution should be implemented into action in a well-planned approach. This book will provide the collective insights of prominent industry leaders, researchers, academicians on how businesses can prepare for the future through innovation, sustainability, and global transformation. Furthermore, this volume bridges cutting-edge research with practical applications to offer actionable strategies for navigating an increasingly complex global marketplace. By fostering interdisciplinary perspectives and sharing rigorous empirical research, this volume proposes forward-thinking solutions designed to guide businesses toward a resilient, responsible, and globally integrated future.

AI-enabled tools are significantly transforming the process of knowledge creation by supporting literature review, predictive analysis, intelligent data processing, and research efficiency. This edited book aims to provide readers with a comprehensive understanding of the opportunities, challenges, ethical concerns, and future prospects associated with artificial intelligence. By integrating theoretical perspectives with practical applications, the volume serves as a valuable resource for scholars, students, policymakers, industry professionals, and researchers interested in understanding the interdisciplinary dimensions of AI.

I sincerely appreciate the efforts of all contributors who have shared their valuable research and intellectual insights in this volume. Their scholarly

contributions have enriched the quality and diversity of this book. I commend the editors Dr. Aanchal Arora, HOD, Department of Chemistry, Khalsa College for Women, Civil Lines Ludhiana, Dr. Khushdip Kaur, Associate Professor, PG Department of Commerce, Khalsa College for Women, Civil Lines Ludhiana and Dr. Isha Dudeja, Assistant Professor, Department of Chemistry, Khalsa College for Women, Civil Lines, Ludhiana and contributors of the book for their rigorous and thoughtful engagement with this important subject. I am confident that this book will encourage deeper inquiry, interdisciplinary collaboration, and critical thinking regarding the transformative role of artificial intelligence in academic research, policy discussions, and practical advancements in the fields of science, humanities, commerce, and management.

Prof. Parmjit Kaur

Ex-Dean of Business Management and Commerce
Ex-Chairperson and Professor
University Business School
Panjab University, Chandigarh.

Contents

Acknowledgement	i
Foreword	iii
1 ARTIFICIAL INTELLIGENCE IN BIOTECHNOLOGY: TRANSFORMING SCIENCE IN THE DATA ERA	1
1.1 Introduction	2
1.2 AI Toolkit in Biotechnology	7
1.3 Applications of AI Across Biotechnological Domains	10
1.4 Real-World Applications and Case Studies of AI In Biotechnology	15
1.5 Challenges and Ethical Considerations In AI-Driven Biotech- nology	18
1.6 Conclusion	22
References	22
2 INTELLIGENT COMPUTING IN BIOLOGY: ADVANCES AND PERSPECTIVES	27
2.1 Introduction	27
2.2 Historical Evolution	29
2.3 Advances In Intelligent Computing Techniques	32
2.4 Applications Of Intelligent Computing	33
2.5 Challenges And Limitations	35
2.6 Conclusion	36
References	37
3 GUARDIANS OF BIODIVERSITY: ARTIFICIAL INTELLIGENCE REVOLUTIONIZING ANIMAL CONSERVATION	41
3.1 Introduction	42
3.2 Foundations Of Artificial Intelligence	44
3.3 Applications of AI In Wildlife Monitoring	47
3.4 AI In Habitat Assessment and Ecosystem Management	50
3.5 Combating Wildlife Crime and Poaching Using Artificial Intelligence	51

3.6	Artificial Intelligence In Disease Surveillance And One Health Approaches	53
3.7	Artificial Intelligence and Conservation Genetics	54
3.8	Case Studies of AI-Driven Conservation Success	55
3.9	Ethical, Social and Technical Challenges	56
3.10	Future Directions and Emerging Technologies	57
3.11	Conclusion	58
	References	58
4	ARTIFICIAL INTELLIGENCE FOR PHYSICAL SCIENCES	61
4.1	Introduction	61
4.2	Applications In Classical Mechanics	63
4.3	Applications In The Field of Electromagnetism	64
4.4	Applications In Statistical Physics	65
4.5	Conclusion	66
	References	66
5	AI TOOLS IN CHEMISTRY	69
5.1	Introduction	70
5.2	Overview of Artificial Intelligence	71
5.3	Why Chemistry Needs AI	74
5.4	Major AI Tools Used In Chemistry	75
5.5	Conclusion	79
	References	81
6	MATHEMATICS BEHIND ARTIFICIAL INTELLIGENCE	85
6.1	Introduction	86
6.2	Mathematical Representation of Data In Artificial Intelligence	87
6.3	Pedagogical and Scientific Significance of Mathematics In AI	93
6.4	Conclusion	94
	References	94
7	AI IN MATHEMATICS AS A TOOL TO SOLVE PROBLEMS	97
7.1	Introduction	98
7.2	The Relationship Between Mathematical Principles And AI .	98
7.3	Methodology of Artificial Intelligence	99
7.4	Problem Solving And Equation Generation	99
7.5	Calculus	100
7.6	Linear Algebra	101
7.7	Theorem Proving	101
7.8	Conclusion	102
	References	102

8	ARTIFICIAL INTELLIGENCE AND LITERATURE: TRANSFORMATIONS, CHALLENGES AND FUTURE	105
8.1	Introduction	106
8.2	Technology and The Evolution of Literature	107
8.3	AI and Literary Creation	111
8.4	Authorship And Originality	111
8.5	Computational Literary Analysis	112
8.6	Distant Reading And Text Mining	112
8.7	Sentiment And Stylistic Analysis	114
8.8	Visualization And Network Analysis	115
8.9	Ethical Issues And Cultural Concerns	116
8.10	AI in Literary Pedagogy	117
8.11	Theoretical Perspectives	119
8.12	Future Directions	120
8.13	Conclusion	120
	References	120
9	ROLE OF ARTIFICIAL INTELLIGENCE IN CLIMATE CHANGE PATTERNS: OPPORTUNITIES, CHALLENGES AND ENVIRONMENTAL SUSTAINABILITY	123
9.1	Introduction	124
9.2	Role of AI In Climate Change: Opportunities In Mitigation Strategies	125
9.3	Environmental Sustainability Through AI	127
9.4	Challenges And Future Directions	127
9.5	Adverse Impacts of AI on The Environment	128
9.6	Conclusion	128
	References	129
10	ROLE OF ARTIFICIAL INTELLIGENCE IN NUTRITION SCIENCES	133
10.1	Introduction	134
10.2	Conceptual Foundations of AI In Nutrition	134
10.3	Application of AI In Nutrition Science	135
10.4	Myths and Reality Regarding AI In Nutrition	136
10.5	Advantages and Disadvantages of AI In Nutrition Sciences	137
10.6	Restrictions of AI In Nutrition	137
10.7	Prospective Paths	139
10.8	Conclusion	139
	References	139
11	FROM CONCEPT TO CONCLUSION: THE ROLE OF ARTIFICIAL INTELLIGENCE TOOLS IN RESEARCH	143
11.1	Introduction	144
11.2	Emergence of AI In Academic Research	144

11.3	AI Powered Tools for Research Writing	145
11.4	Limitations and Ethical Concerns of AI In Research	150
11.5	Conclusion	151
	References	151
12	LEVERAGING ARTIFICIAL INTELLIGENCE TO TRANSFORM	
	MARKETING PRACTICES	153
12.1	Introduction	154
12.2	AI Applications In Marketing	155
12.3	AI Trends In Marketing	155
12.4	Ethical Concerns Relating To The Use of AI	159
12.5	Conclusion	160
	References	160
13	ARTIFICIAL INTELLIGENCE (AI)- POWERED ACCOUNTING IN	
	INDIA: APPRAISING SOFTWARE SOLUTIONS, THE PERKS AND	
	COMPARATIVE BENEFITS OVER CONVENTIONAL METHODS	163
13.1	Introduction	164
13.2	Literature Review	166
13.3	Artificial Intelligence-Based Accounting Software Solutions	
	IN INDIA	167
13.4	Advantages of AI Compared To The Traditional Approaches .	171
13.5	Applications In Multinational Companies	172
13.6	Accounting Professionals Have A Role Transformation	176
13.7	The Hybrid Model: Future of Accounting	176
13.8	Conclusion	177
13.9	Predictions For 2030	178
13.10	Recommendations	179
	References	180
14	ROLE OF ARTIFICIAL INTELLIGENCE IN THE BANKING	
	SECTOR: A SYSTEMATIC LITERATURE REVIEW	183
14.1	Introduction	183
14.2	Review of Literature	184
14.3	Methodology	187
14.4	Analysis And Findings And Systematic Literature Review . .	188
14.5	Conclusion	188
	References	189
15	THE ADOPTION OF ARTIFICIAL INTELLIGENCE AND JOB	
	REPLACEMENT: AN HUMAN RESOURCE MANAGEMENT	
	PERSPECTIVE	191
15.1	Introduction	192
15.2	Research Design	194

15.3	Literature Review	195
15.4	AI-Loss of Jobs: Analysis And Affected Jobs	196
15.5	Artificial Intelligence Perks In The Workplace	200
15.6	Human Resource Management: Problems And Potentiality .	202
15.7	Future of Work: In The Age of AI, Skills And Reskilling	204
15.8	Implications And Recommendations	205
	References	206

Chapter 1

ARTIFICIAL INTELLIGENCE IN BIOTECHNOLOGY: TRANSFORMING SCIENCE IN THE DATA ERA

Simerpreet Kaur

Assistant Professor, Department of Biotechnology, Khalsa College for Women, Civil Lines, Ludhiana, Punjab, India-141001.

Email: s.simer118@gmail.com

Abstract

Artificial intelligence (AI) has significantly reformed human life and scientific research, making the world more digital. In biology, the “AI Revolution” has shifted the field from observational to a predictive and programmable engineering science. By merging AI with biology, researchers are able to handle the “complexity crisis” in biological data that easily surpass human analysis. Deep learning, machine learning and data science, are widely used to understand, model and work with biological systems. Biotechnology plays a huge role in the development of products and technologies that enhance our lives by utilizing the biological systems, organisms and biomolecules. The large and complex data generated is processed with the support of AI swiftly and cost effectively. Biotechnology has wider applications in pharmaceuticals, agriculture, industrial enzymes, diagnostics and environmental solutions. One of the most important developments by the use of AI in biotechnology is the ability to predict protein structures, accelerates manufacturing of antibodies and enzymes and improves drug design. AI has also helped to quickly produce mRNA vaccines by analyzing viral genome sequences and optimizing mRNA codons. AI-powered biosensors are improving food safety, environmental monitoring and medical diagnostics. Other areas where AI is making a difference include agricultural

biotechnology, bioprocess engineering and metabolic engineering. Interdisciplinary collaboration of biological science and AI methodologies is actively changing the conception, development and application of biotechnological innovations.

Keywords: Artificial Intelligence (AI), Biotechnology, Biological Science, Data Science, Machine Learning

1.1 Introduction

The advent of the “AI Revolution” has fundamentally recalibrated the trajectory of biological science. One of the most groundbreaking events in the modern science is the convergence of artificial intelligence (AI) and biotechnology. Though historically biotechnology has been driven forward in experimental molecular biology, genetic engineering, and high-throughput screening, the rapid growth of biological data has demanded computational frameworks in the management of complexity at a scale never before seen. AI has not only become an analytical assistant but also a structural force that will transform the way biological knowledge is produced, understood, and applied to therapeutic and industrial practice. The applicability of AI in biotechnology was especially striking with the growth of biological datasets that were growing exponentially due to the development of the next-generation sequencing and high-throughput experimentation. Machine learning and deep learning techniques have become a powerful computational model in data-intensive fields, particularly in artificial intelligence. Neural networks and deep learning designs made the extraction of feature hierarchies of high-dimensional data, overcoming the traditional statistical models in pattern recognition tasks (LeCun et al., 2015). Machine learning systems enable systems to discover complex input-output relationships based on empirical data instead of being based on mechanistic rules (Jordan and Mitchell, 2015). Thus, the modern AI revolution cannot be identified only by the innovation of an algorithm but rather by its application in scientific discoveries.

1.1.1 Convergence of AI and Biotechnology

The complexity of biological systems is rising, and AI implementation in biotechnology provides a solution. Biological processes have

nonlinear interactions among many levels of organization such as regulation of genes and protein folding, cellular signalling and phenotypes of organism. These multiscale dependencies are difficult to model using traditional linear statistical models. The application of AI can be used to make predictive modelling in various biological areas. Deep learning systems have already been shown to be capable of inferring protein structures using amino acid sequences with near-experimental accuracy (Jumper et al., 2021), predicting regulatory effects of genomic variants with accuracy (Zhou and Troyanskaya, 2015), and speeding up drug discovery pipelines (Vamathevan et al., 2019). These are some accomplishments that portray that descriptive biology is giving way to predictive and design-driven biotechnology. Notably, AI not only improves analytical ability, but also translational efficiency. Computational models reduce the use of expensive trial-and-error research by giving experimental candidates a priority and incorporating multimodal data. Such a predictive prioritization helps to become more productive in terms of RandD in the pharmaceutical and industrial biotechnology industries (Paul et al., 2010). AI and biotechnology intersect in this way as a larger drop is also viewed in terms of the Fourth Industrial Revolution, where the digital and biological worlds are being merged (Schwab, 2016). In this paradigm, labs are increasingly being run in bio-digital ecosystems in which algorithmic modelling, robotics and high-throughput experimentation are synergistically interacting. This chapter discusses AI-based biotechnology as systemic change and not a series of applications. It discusses that machine learning and deep learning structures approach biological complexity, integrate multi-omics, accelerate drug discovery, improve precision medicine, and transform synthetic biology. Besides, it critically assesses ethical, regulatory and societal issues related to AI integration.

1.1.2 AI–Biotechnology Interface: Addressing the Complexity Crisis

Artificial intelligence (AI) in biotechnology is a recent development as a reaction to a growing complexity crisis in the life sciences. The contemporary biological systems are nonlinear, interactive, hierarchical, and stochastic in the expression of the genes and multiscale regulatory networks. The analytical difficulties have been exacerbated even more by the rapid growth of high-throughput

technologies, where the amount of data produced by them is beyond the power of conventional statistical and experimental models. AI can be applied to this interface as a computational infrastructure, which is capable of modelling biological systems at high dimensions, combining heterogeneous data, and enhancing translational discovery.

Systems-Level Complexity in Biological Sciences

Biological systems are systems of networks and non-linear pathways. The importance of systems biology is that the cellular functions are brought about by dynamic interactions between genes, proteins, metabolites, and signalling networks (Kitano, 2002). Network studies reveal that cellular networks have scale-free structures, in which central nodes that have the highest number of connections control system stability and disease susceptibility (Barabasi and Oltvai, 2004). These networked systems make reductionist experimentation difficult. Modulations in a single molecular constituent can be transduced along feedback loops and cross-regulatory networks, and they yield nonlinear results. Moreover, the variability brought about by the stochastic gene expression at the single-cell level makes it harder to determine how deterministic models work (Raj and Van Oudenaarden, 2008). Differential equation-based traditional mathematical models become more and more intractable as the dimensionality of the system increases. AI techniques, especially deep neural networks, overcome this weakness by discovering nonlinear mappings that are complex and do not need a mechanistic specification based on empirical evidence (LeCun et al., 2015). This change in mechanistic abstraction to data-driven modelling is radical in biological inference.

1.1.3 Data Explosion in Omics Technologies

The innovations in next-generation sequencing (NGS) have significantly enlarged the quantity and quality of biological data. Entire-genome sequencing, transcriptomics, proteomics, metabolomics and single-cell analyses result in huge, high-dimensional information (Metzker, 2010). Individual-cell RNA sequencing, such as one example, allows one to profile gene expression in cells, and this provides heterogeneity that would be hidden in bulk measurements (Tang et al., 2009). Although such technologies can be used to

gain a greater biological understanding, they also create analytical bottlenecks. Ordinarily, high dimensionality, sparsity, batch effects, and measurement noise make the inference of statistics difficult. These issues are especially the most appropriate to be handled with machine learning models, as they can establish latent structures and correlations without having prior hypothesized outcomes (Libbrecht and Noble, 2015). Additionally, integration of multi-omics, i.e. the integration of genomic, transcriptomic and proteomic data, demands the harmonization of heterogeneous data modalities. Embedding methods based on AI and integrative modelling systems can allow cross-platform data fusion to allow systems-level biological interpretation. Therefore, the growth of omics technologies has not only augmented the quantity of data, but it has also required AI-based computational infrastructures that can produce biological signals.

Recent advances in this direction eloquently demonstrate how multimodal and multi omics data may be combined with transformer buildings that harmonize genomic, transcriptomic and proteomic data in shared latent spaces (Subramanian et al., 2022). These advanced techniques do not only enhance systems level inference, but also to enhance predictive robustness across biological datasets of non-identical components in the famous way, which strengthens, productivity-wise, molecular biology as the computational mainstay of integrative biotechnology.

Limitations of Traditional Experimental Approaches

Traditional biotechnology studies have been based on the hypothesizing experimental and validation via incremental validation. Although these methods are often rigorous in a methodological sense, they can be time-consuming and exploratory in nature. The case of drug discovery is an illustration of such limitations, as the rate of attrition is high and development time is prolonged (Paul et al., 2010). Another weakness that is demonstrated by genome-wide association studies (GWAS) is that they only detect statistical correlations between genetic variants and disease phenotypes, but in most cases do not capture higher-order interactions and epistatic effects (Visscher et al., 2017). Linear modelling systems have difficulty in capturing combinatorial interactions between more than two loci. Also, there have been worries in matters of reproducibility in biomedical research (Ioannidis, 2005). Unreliable findings are caused by small

sample sizes, selective reporting and statistical overfitting. With adequate cross-validation and independent datasets, AI models provide scalable frameworks of robust predictive modelling. Notably, AI does not eliminate experimental biology; it simply rearranges it. Predictive models rank candidates of experiments, reduce search space and optimize resource wastage. Due to the incorporation of in silico prediction and empirical validation, there are minimized inefficiencies brought about by the conventional trial-and-error experimentation.

AI: Tool for Pattern Recognition and Predictive Modelling

The most important one is predictive capability, which is contributed by AI at the interface with biotechnology. Machine learning systems convert descriptive biology information into predictive machine learning systems, which can predict molecular functions, disease susceptibility, and treatment outcome. Deep learning systems determine the sequence of a protein and predict its structure (Jumper et al., 2021), determine the regulatory consequences of noncoding variants (Zhou and Troyanskaya, 2015), and estimate drug-target interactions (Vamathevan et al., 2019). These predictive systems allow prioritizing translational pipelines in advance, at a faster rate. Moreover, AI helps to generate hypotheses through finding latent relationships in massive datasets. Network methods combine data of molecular interactions to reveal disease modules and possible therapeutic targets (Barabasi et al., 2011). This evolution of hypothesis discovery based on data is a divergence away from theory-based experimentation. AI is more efficient at translational research by offering time-saving in discovery, and allowing integrative analysis across scales of molecules. Such predictive infrastructures are becoming increasingly important to the biotechnology sector to sustain innovation productivity.

The interface between AI and biotechnology comes as a consequence of the necessity to handle the biological complexity and data proliferation. Systems-level interactions, stochastic variability and multi-omics integration are beyond the analytical ability of conventional methodologies. AI gives scalable, nonlinear modelling structures that can be used to produce useful biological information out of high-dimensional data. The integration of data to predict what is to be made, experimental prioritization, and predictive

modelling make AI turn biotechnology into an enterprise that is more of a calculation than a mostly empirically driven field. The AI-biotechnology interface will be at the core of the further scientific development, as the biological data will only grow in size and diversity.

1.2 AI Toolkit in Biotechnology

The incorporation of artificial intelligence (AI) into biotechnology is premised on a collection of computational approaches aimed at simulating high-dimensional, nonlinear biological systems. In contrast to the classical methods of statistics, current AI systems allow hierarchical learning of features, integration of multiple modalities of data, and prediction modelling of genomic, proteomic, and phenotypic data. The biotechnological AI toolkit can be viewed, then, not as a general-purpose computational paradigm, but as a domain-specific methodological architecture that is tailored to the complexity of biology as a domain.

1.2.1 Machine Learning in Biological Data Analysis

Machine learning (ML) is the basis of the analytical engine of AI-based biotechnology. ML algorithms are able to represent patterns based on data without a defined rule-based programming language, so they are especially efficient with large-scale omics data, which is nonlinear in nature and has high dimensions (Jordan and Mitchell, 2015). Genomics supervised learning is commonly applicable to classification and regression. As an example, genomic annotation based on supervised models is used to predict the deleteriousness of genetic variants in prediction frameworks of pathogenicity (Kircher et al., 2014). Applied to protein biology, deep learning models with respect to labelled sequence datasets predict DNA and Unbinding specificities directly as an input of raw sequence (Alipanahi et al., 2015). These utilities are a demonstration of how supervised learning is used to convert unstructured biological sequences to viable forecasts. Learning without supervision assists in dimensionality reduction and clustering of large data sets. The clustering algorithms are necessary in single-cell transcriptomics, where thousands of cells are being produced with expression profiles, and subpopulations of cells are determined (Tang et al., 2009). These techniques disclose cellular heterogeneity, which otherwise would not be visible using

bulk analysis. The reinforcement learning, less widespread in the conventional bioinformatics, has gained significance in molecular design. The frameworks of reinforcement learning optimize chemical structure through the repeated maxims of the predicted biological activity or drug-likeness (Zhavoronkov et al., 2019). This goal-oriented optimisation is a change in the equilibrium of prediction to a dynamic design.

1.2.2 Deep Learning Architectures for Biological Systems

As a subfield of machine learning, deep learning has become a fundamental part of biotechnology owing to its capacity to discover hierarchical representations of raw data on its own (LeCun et al., 2015). The biological system is characterized by multiscale dependencies, such as those between the nucleotide motifs and the three-dimensional protein conformation, so deep architectures are especially appropriate. Convolutional neural networks (CNNs), which were initially created to process images, are generally used to analyse genomics sequences. CNNs identify local sequence motifs that are predictive of regulatory activity or protein binding (Alipanahi et al., 2015). DeepSEA also revealed that using DNA sequence only, deep convolutional models are able to predict chromatin accessibility and transcription factor binding (Zhou and Troyanskaya, 2015). Attention mechanisms in the Transformer architecture, which has attention mechanisms, have also improved sequence modelling. These models can also learn long-range reactions in sequences, making them superior enough to breakthroughs like the highly accurate prediction of protein structure in AlphaFold (Jumper et al., 2021). The attention mechanisms enable the models to be characterized by a complicated interaction between amino acid residues in space, which is important to structural biology. Therefore, deep learning is not only limited to classification, but also to the modelling of complex biological structures and interactions.

With the development of evolutionary-scale biological sequence foundation models has come the emergence of new structural and functional inference capabilities which are beyond traditional supervised paradigms (Nijkamp et al., 2023). These large protein language models are redefining the learning of biological representation in AI-based biotechnology through scaling laws and self-supervised learning, and are discovering new directions.

1.2.3 Generative Models and Design-Oriented AI

The generative AI models are a paradigm shift between predictive analytics and synthetic design. Computational generation of new molecular and protein structures is possible with variational autoencoders (VAEs) and generative adversarial networks (GANs), as well as reinforcement learning-based generative frameworks. Generative deep learning platforms are used in drug discovery to develop molecules that are optimized in terms of their potency, selectivity, and pharmacokinetic properties (Zhavoronkov et al., 2019). Generative models have been used in protein engineering to propose variants that are more stable or active in sequence space (Anand and Huang, 2018). These systems increase the available space of biological design, over and above current empirical libraries, and thus, shorten the time taken to innovate and minimize the screening of experiments.

1.2.4 Explainable AI and Model Transparency

Although AI has predictive ability in the field of biotechnology, it needs to solve the issue of interpretability. Deep learning models are thought of as black-box and this discourages their use in the clinical and regulatory setting. The goal of explainable AI (XAI) methods is to measure the importance of the features and give interpretable results of the models. SHAP (Shapley Additive Explanations) is a theoretically based tool of interpretation model prediction, which assigns contributions of input features (Lundberg and Lee, 2017). Interpretable deep learning models can be used in genomics to discover particular sequence motifs that mediate regulatory predictions (Zhou and Troyanskaya, 2015). The issue of balancing predictive performance and interpretability is a major methodological problem. The transparency is essential in high-stakes cases like gene editing or clinical diagnostics, as it is vital to regulatory acceptance as well as the ethical acceptance.

A combination of these approaches facilitates a high-dimensional approach, multimodal information combination, and predictive biological design. Instead of substituting experimental biology, AI supplements it, as an example of taking on computational foresight voyage over hypotheses, molecular engineers optimally, and ultra-quick translational research. As models are made more

interpretable and data structures are more robust, AI will remain a methodological pillar in the contemporary biotechnology.

1.3 Applications of AI Across Biotechnological Domains

Artificial intelligence (AI) has ceased to be a facilitated approach to computationalism and has become a key focus of innovation in biotechnology. It finds use in structural biology, pharmaceutical science, genomics, gene editing, industrial biotechnology, agriculture, diagnostics and synthetic biology. The disruptive nature of AI is due to its ability to represent nonlinear interactions in biology, combine heterogeneous data and produce predictive information at scales that were impossible before using traditional methods of experimentation.

1.3.1 Protein Structure Prediction and Structural Biology

One of the most dramatic applications of AI in biotechnology that has been shown to date is protein structure prediction. The biological activity and its enzymatic activity, as well as the molecular interactions of any protein, depend on its three-dimensional conformation. Traditionally, the identification of protein structures was done through X-ray crystallography, nuclear magnetic resonance (NMR) spectroscopy or cryo-electron microscopy, services that are both resource-demanding and time-consuming. This field has undergone the revolution in deep learning. DeepMind created AlphaFold2, which performed almost at the level of experiment in predicting protein structures during the Critical Assessment of protein Structure Prediction (CASP14) challenge (Jumper et al., 2021). AlphaFold2 uses neural network architectures based on attention and captures long-range interactions of amino acids using attention. With a combination of evolutionary data provided by several sequence alignments and deep neural representations, the model provides stunning precision in the conservation of atomic coordinates. This breakthrough cannot be limited to structural determination. The correct method of structural prediction increases functional annotation, rational drug design and enzyme engineering. In their work, Baek et al. (2021) proposed another deep learning-based system, RoseTTAFold, which can also be used to structure modeling in high accuracy. This has made structural biology democratic with the extensive availability of predicted protein structures through

open databases, allowing investigators all over the world to gain access to structural information in the absence of experimental infrastructure. In addition, AI protein modelling can be used to understand intrinsically disordered proteins and protein-protein interactions. All these developments can be described as a paradigm shift in structural biology, with computational prediction currently complementary to and, in certain cases, a prior to experimental validation.

1.3.2 Drug Discovery and Rational Drug Design

The discovery of drugs has long been marked by expensive and lengthy time and high turnover. AI has become a key instrument to fight inefficiencies in the pharmaceutical pipeline. Machine learning algorithms help to identify targets, screen virtually, molecularly dock, predict pharmacokinetics, and predict toxicity (Vamathevan et al., 2019). Deep learning-based de novo molecular design can be seen as one of the transformative applications. The reinforcement learning models and generative adversarial networks (GANs) are designed to produce new chemical designs that have specific biological attributes (Zhavoronkov et al., 2019). Zhavoronkov et al. (2019) showed that potent DDR1 kinase inhibitors may be identified quickly through AI-based generative chemistry, which minimizes the time spent on candidate discovery. Prediction of drug-target interactions is also increased by AI. GNN frameworks represent molecular structures in the form of graphs, including interactions and chemical bonds among atoms (Gilmer et al., 2017). These architectures enhance the predictive quality of the structure-activity relationship (SAR). Besides, AI facilitates repurposing of drugs through biomedical literature and clinical data mining. The potential therapeutic candidates in the COVID-19 pandemic were identified through machine learning-based analysis of the existing drug libraries (Morselli Gysi et al., 2021). These strategies highlight the fact that AI can react to an emerging health crisis quickly. Pharma companies are progressively incorporating AI platforms to minimize the expenditure incurred during the research and development and to fast-track clinical translation. Nevertheless, there are still issues of data bias, model interpretability and regulatory compliance.

1.3.3 mRNA Vaccine Development and Immuno-informatics

The accelerated production of mRNA vaccines in response to the COVID-19 pandemic features the importance of computational immunology and AI-based antigen design. To develop the vaccine, there should be immunogenic epitopes that will induce a strong immune response. The models of machine learning predict T-cell and B-cell epitopes given the viral protein sequences, which optimize the vaccine design (Reynisson et al., 2020). Artificial intelligence (AI) applications like NetMHCpan can be used to predict the affinity of a peptide to the major histocompatibility complex (MHC), which is an important factor of immunogenicity. Moreover, mRNA vaccine stabilization plans were based on structural modelling of viral spike proteins (Wrapp et al., 2020). The use of AI-enhanced protein structure prediction allowed quick determination of conformational epitopes, which made it possible to engineer antigens rationally. mRNA vaccine vectors have the advantage of AI optimization of codon usage, RNA stability, and lipid nanoparticle delivery systems. Computational modelling application in immune informatics shortens the schedule of vaccine development and increases predictive effectiveness.

1.3.4 Genomics and Precision Medicine

Precision medicine is based on the combination of genomic, transcriptomic, and clinical data to customize therapeutic intervention. The AI-powered genomics is capable of determining pathogenic variants, polygenic risk scores, and gene-disease relationships. Noncoding variants have had functional consequences predicted using deep learning models. DeepSEA by Zhou and Troyanskaya (2015) predicts the effects of the chromatin and regulatory functions based solely on the DNA sequences. These models improve on the interpretation of variants that have been found using genome-wide association studies (GWAS). Cancer genomics is also made possible by AI. Ciriello et al. (2013) used computational modeling to determine oncogenic pathway changes in various tumor types, which supports individual oncology plans. Machine learning models combine the profiles of somatic mutations and transcriptomic data in the prediction of therapeutic responses. Large-scale projects like the UK Biobank produce multimodal data sets consisting of genetic, phenotypic and imaging data. These datasets are fed to AI models to identify the risk of disease and stratify the patients (Bycroft et al., 2018). Precision

medicine is thereby a good example of how AI can transform genomic information into clinically actionable information.

Models of generative and diffusion based molecular design have catapulted de novo therapeutic development to a new phase of development as it can be used to generate chemically valid and synthesizable compounds at scale (Walters and Murcko, 2023). Simultaneously, CRISPR optimization with the aid of deep learning raises the accuracy of genome editing, significantly increasing the on-target efficiency and reducing the off-target risk.

1.3.5 Gene Editing and CRISPR Optimization

Gene editing has become a revolution with CRISPR-Cas systems. Nevertheless, an effective design of guide RNA (gRNA) and reducing off-target effects are important problems to be optimized. On-target efficiency and off-target specificity prediction in machine learning models are based on sequence features. Doench et al. (2016) trained predictive models to be the best guide to single-guide RNA (sgRNA) activity, that is, to increase the accuracy of editing. In the same way, the deep learning models like DeepCRISPR combine the sequence and epigenomic features to enhance gRNA design (Chuai et al., 2018). In the case of AI, the models determine the possible sites of off-target cleavage in the genome, which minimizes unintentional genomic alterations. These forecasting systems heighten the security and effectiveness of gene therapies. CRISPR, coupled with AI convergence, increases the precision of genome engineering, which can be used to treat diseases and enable agricultural biotechnology.

1.3.6 Industrial Biotechnology and Bioprocess Engineering

Industrial biotechnology entails large-scale production of bio-based chemicals, pharmaceuticals and biofuels. AI optimizes conditions of fermentation and distribution of metabolic fluxes and process control. Machine learning frameworks forecast the work of the bioreactors and anticipate anomalies in real time. Indicatively, data-based modelling can be used to optimize yields in microbial fermentation systems (Nielsen and Keasling, 2016). Predictive analytics can assist in the adaptive control of strategies, which will help waste less resource and produce more output. The AI-based metabolic modelling combines the genome-scaled metabolic network with the production data to optimize the pathways. Machine learning

and constraint-based modelling are used to detect the bottlenecks in industrial strains. Industrial biotechnology can be made more efficient, sustainable, and scalable with the use of AI in bioprocess engineering.

1.3.7 Antibody and Enzyme Engineering

Structural modelling and affinity prediction are useful in antibody engineering due to AI usage. Deep learning models make predictions available on antibody-antigen interactions, making it possible to rationalize affinity maturation. Mason et al. (2021) showed that optimizing the sequences of antibodies with the help of deep learning made the process of developing therapeutic antibodies much faster. Categorically, enzyme engineering also uses generative models to create versions with better stable conditions or catalytic activity. AI is used to reduce the number of screenings required to screen many candidates experimentally by computational culling of candidate variants before experimental validation.

1.3.8 Agricultural Biotechnology

AI develops crop genomics, prediction of traits, and resiliency to stress. Machine learning is used to combine genomic markers with phenotypic traits to speed up breeding in plants (Crossa et al., 2017). Remote sensing and computer vision are used to assess the health of crops, diagnose diseases, and forecast the yield. Artificial intelligence is used in predictive breeding designs to enhance drought resistance and disease resistance. The food security and the climate resilience of agricultural biotechnology application of AI are complementary.

1.3.9 Biosensors and Diagnostic Systems

AI improves biosensors' signal-reading as well as diagnostics. Elaborate learning algorithms examine microscopic and radiological imaging data in order to identify disease biomarkers (Esteva et al., 2017). Biosensors used on the body produce streams of physiological data. Machine learning detects anomalies that are a sign of disease states. Diagnostic platforms are point-of-care platforms that combine AI to interpret biochemical signals in an optimal and fast way to enhance early detection and personalized healthcare.

1.3.10 Metabolic Engineering and Synthetic Biology

Synthetic biology is a field that combines computer design and biological design. The AI models replicate metabolic networks and forecast optimal adjustments to the pathways (Nielsen and Keasling, 2016). Generative models create artificial gene networks and gene regulation and can be used to create programmable biological systems. The optimization of pathways by AI increases the generation of value metabolites. The introduction of AI to synthetic biology is changing the biological design paradigm as a trial-and-error process to one that is computationally engineered.

1.4 Real-World Applications and Case Studies of AI In Biotechnology

The most evident practical effects of AI in biotechnology are translational applications where computational modeling is complemented by biological experimentation. Although previous sections discussed methodological bases and domain-specific examples, the practical application of AI platforms to the predictive systems in the pharmaceutical development, structural biology, and synthetic bioengineering is highlighted in the real-world case studies. These platforms represent integrated and closed-loop systems rather than discrete computational systems, which include data generation, algorithmic modelling, and experimental validation.

1.4.1 AI-Driven Drug Discovery Platforms

There are AI-driven drug discovery firms that have operationalized machine learning and generative modelling in the drug pipeline. The discovery of discoidin domain receptor 1 (DDR1) kinase inhibitors through a deep generative reinforcement learning architecture was one of the brightest examples of this strategy (Zhavoronkov et al., 2019). In this research, AI-based candidate molecular structures were optimized towards biological activity, pharmacokinetic and chemical feasibility, leading to long-term shortenings in the discovery timeline in the early stages. In contrast to the conventional high-throughput screening, which involves physical screening of large compound libraries, AI-based systems perform virtual screening of large chemical spaces. Machine learning models based on structure-activity relationships predict molecular binding affinity

and toxicity before they are synthesized (Vamathevan et al., 2019). Such computational preference lowers the load on the experiment and the efficiency of RandD. Drug repurposing is also supported by network-based computational medicine. Through the network of molecular interactions and disease modules, AI systems are able to find existing drugs that have therapeutic potential in new applications (Barabasi et al., 2011). The use of network-based modelling methods during the COVID-19 pandemic has also helped in the fast discovery of candidate repurposed drugs (Morselli Gysi et al., 2021) as an example of the dynamic response of AI to emerging biomedical disasters. Together, these platforms show that AI can help decrease the attrition rates, speed up the process of prioritizing the candidates, and incorporate multi-omics data into pharmaceutical development ecosystems.

1.4.2 AI in Structural Biology and Protein Engineering

One of the most impactful instances of AI translational influence is the application of the deep learning to structural biology. The almost experimental accuracy of the AlphaFold in predicting the structure of proteins (Jumper et al., 2021) is a breakthrough in computational biology. The system was able to solve a several-decades-old scientific problem by modelling long-range interactions of residues using attention-based architectures. The wider effect of this success is that it is integrated into the research infrastructure in the world. The availability of millions of predicted protein structures has allowed the rapid functional annotation of proteins, drug discovery involving structures, and enzyme engineering. Supplementary deep learning fields, like RoseTTAFold, have supported the accuracy of AI-based structural modelling (Baek et al., 2021). Structural predictions are used to guide rational strategies of modification in protein engineering contexts to minimize the use of empirically-driven mutagenesis. The merging of structural AI in the biotechnology pipelines is, therefore, just an example of the direct use of algorithmic innovation in improving the productivity of experimental processes.

1.4.3 AI-Based Phenotypic Screening and Systems-Level Discovery

Another paradigm that can be used in place of target-based discovery is AI-guided phenotypic screening. Deep learning and high-content

imaging can be used to quantitatively describe morphological reactions of cells to chemical perturbations. Convolutional neural networks (CNNs), which were initially designed to perform computer vision, detect high-dimensional features in microscopy data, and therefore, allow classifying delicate phenotypic signatures (Esteva et al., 2017 and LeCun et al., 2015). Phenotypic AI systems record complicated cellular reactions that are manifestations of multicellular pathway actions as opposed to single-target modulation. This is a systems-level method that is consistent with the principles of network medicine, in that disease phenotypes are a result of perturbations in interacting molecular networks (Barabasi et al., 2011). Phenotypic platforms make it possible to discover many hypotheses at a time by combining automated imaging, robotics, and machine learning. These systems enlarge the drug discovery to cover other approaches that do not consider a particular target molecule but aid in discovering compounds that can reproduce disease-related cellular phenotypes.

1.4.4 AI-Enabled Synthetic Biology and Biomanufacturing

Synthetic biology systems involve the use of AI to combine predictive and automated laboratory systems used to optimise biological design. Rational strain engineering is directed by computational metabolic modelling by finding pathway bottlenecks and resource allocation trade-offs (Nielsen and Keasling, 2016). Machine learning designs evaluate the results of experiments and advance genetic designs through cycles of design-build-test-learn. Such combined systems improve the optimisation of yield in biotechnology in the industry and shorten the development cycles of engineered organisms. Instead of the full application of empirical screening, predictive models run on AI-based platforms reduce the size of the experimental search space. Semi-autonomous experimental ecosystems are emerging because of the warming of principles of robotics, high-throughput DNA synthesis, and machine learning analytics. The trend toward computationally directed biological manufacturing is depicted by such systems. The practical application of AI to biotechnology is also associated with a change in the computational support of innovation to an algorithmic-driven innovation ecosystem. With or without generative drug design and or structural prediction, phenotypic screening and or metabolic optimisation, AI platforms

merge inference with experiments via closed-loop systems where data is fed in, and results are fed out. Through the examples of these case studies, it can be seen that AI is not simply improving the steps of individual technology fibre of a biotechnology system; it reshapes the very architecture of discovery. Through time-to-candidate time reduction, enhanced predictive performance and scalable biological design, AI-based systems promise transformation of the bio-digital innovation paradigm, transforming the paradigm of translational biotechnology.

1.5 Challenges and Ethical Considerations In AI-Driven Biotechnology

The implementation of artificial intelligence in the field of biotechnology can bring transformative potential, but it also provides a complex set of ethical, methodological, and regulatory problems. With the more widespread use of AI systems in drug discovery, interpreting genomics, clinical decision-making, and synthetic organism design, the necessity to implement AI in a responsible manner emerges. Alongside the challenges linked to the functioning of AI-based biotechnology, AI-based biotechnology presents, in addition to technical functionality, an issue of data bias, interpretability, privacy, biosecurity, regulatory governance, and intellectual property. It is vital to address these issues to maintain the level of trust in the population, scientific integrity, and fair innovation.

1.5.1 Data Bias, Representativeness, and Reproducibility

AI systems are essentially data-conscious, and their capability and generalizability are limited by the representativeness and quality of training data. A skewed population sample in reference datasets creates a great deal of equity risks in genomics and precision medicine. Cohort-based polygenic risk scores that are, consequently, mostly of European ancestry show a reduced predictive power in underrepresented groups, which could further promote the health disparities faced by the world (Martin et al., 2019). In addition to representativeness, biological data usually possess technical noise, batch effects and measurement variance. Omics data especially high-dimensional data is prone to overfitting in the event of poor model validation (Libbrecht and Noble, 2015). The reproducibility crisis in biomedical research is further enhanced, making the use

of AI tools complicated (Ioannidis, 2005). Without standardized reporting, transparent model documentation and independent validation, predictive systems have the risk of not being able to generalize to other contexts. The mitigation strategies then involve the incorporation of varying datasets, a cross-validation framework, external benchmarking and open-data programs. Responsible AI in biotechnology thus implies the strict methodological discipline to ascertain reliability and fairness.

1.5.2 Interpretability and Clinical Trust

Deep learning models may be much more accurate at prediction, but they are usually not transparent. The black-box opaque systems used in clinical and therapeutic environments compromise interpretability and are a detriment to regulatory values. The healthcare decision-making requires no ambiguous reasoning structures, except AI outputs informing how to be diagnosed, select treatment choice, or any form of gene-editing. Explainable AI (XAI) techniques seek to estimate the importance of features in the model predictions. SHAP (Shapley Additive Explanations) provides a theoretically based mechanism of assigning predictive power to the input variables (Lundberg and Lee, 2017). Interpretable deep learning models have been used in genomics to predict sequence motifs that have regulatory functionality associations (Zhou and Troyanskaya, 2015). Nonetheless, the post-hoc interpretability methods might be inadequate in the characterization of complicated internal model dynamics. The balance between predictive performance on its part and a mechanistic transparency is an issue of concern. The need to have interpretable systems is also strengthened by the trend where regulatory agencies focus on the transparency of algorithms applied to AI-based medical tools.

1.5.3 Privacy Concerns in Genomic Data

The genomic data is a singularly sensitive type of information with personally identifiable and hereditary data. The anonymized genomic data can be re-identified by computational cross-referencing even in an anonymized form (Gymrek et al., 2013). The combination of genomic, clinical, and phenotypic data using AI increases the possibility of re-identifying and violating privacy. Massive biobank projects enable AI-powered precision medicine, but require powerful

data governance systems (Bycroft et al., 2018). The control of information is defined as ethical custodianship of data, which entails safe storage of data, encryption policies, and informed consent. Privacy-preserving substitutes, including federated learning, in which models are trained on decentralized datasets, and no raw data is shared, are emerging computational methods. Genomic privacy must be ensured to not only protect individuals but also ensure the continuity of public involvement in biomedical research.

1.5.4 Regulatory Governance and Intellectual Property

Artificial intelligence regulatory biotechnology is still in development. The system and protocols of traditional approaches were tailored to an inertial concept of medical equipment and drugs rather than adaptive algorithms integrated inside the algorithm that can learn and evolve through time. The regulatory agencies have suggested the control systems of AI-driven software in the medical field, highlighting the transparency of post-market surveillance and transparency of performance (U.S. FDA, 2019). There are more problems associated with intellectual property structures. The AIs designed to generate molecules, protein designs, and synthetic constructs are to put into doubt questions of inventorship and ownership. Current patent regimes presuppose human authorship, but the generative AI platforms can independently generate new designs made of life. To increase clarity on legal responsibility and ownership rights will be necessary with the growth of AI-driven innovation. Finding the balance between regulatory stringency and flexibility in innovation, thus, is a difficult policy to strike.

The rapid development of AI-driven biological design has increased the biosecurity and governance issues, especially on the dual-use potentials of generative biological models (Kumar et al., 2023). As a result, the international health-policy designs are more and more advocating systematic monitoring tools to promote the responsible introduction of artificial intelligence in biomedical research (WHO, 2023).

1.5.5 Biosecurity and Dual-Use Considerations

Synthetic biology, with the help of AI, is characterised by two sets of risks: the dual usage. In theory, generative models that can produce optimised proteins or genetic constructs may be abused and

used to create dangerous biological agents. Biological design is also becoming less technical as AI tools are democratised, which increases the dangers of biosecurity. To ensure accountable governance, the presence of well-established screening and oversight systems in DNA synthesis, and worldwide cooperation is necessary in a bid to curb the risk of abuse (O'Brien and Nelson, 2020). Proactive biosecurity approaches need to keep up with the pace of AI, as AI increases the ability to design biologically. Biotechnology based on AI is at the border between scientific innovation and moral duty. The presence of data bias, the loss of interpretability, privacy risks, regulatory ambiguity, intellectual property ambiguity, and biosecurity risks, all influence the state of governance of AI-enabled biological research. The solution of these issues does not reduce the transformative potential of AI; on the contrary, it can guarantee its sustainable and fair development. To have proper integration of AI into biotechnology, computational scientists, biologists, ethicists, policymakers, and regulatory bodies should work together in an interdisciplinary manner. Ethical foresight and sound governance will decide whether the bio-digital revolution will be legit in the long run and how it will affect society as AI is more fully integrated into the biotechnology value chain.

1.5.6 Workforce Transformation and Skill Requirements

The introduction of AI into biotechnology transforms the need of workforce. Wet-lab biologists are increasingly gaining the need to become computational, and data scientists are forced to learn the biology. Such an interdisciplinary convergence requires novel education systems. Automation and AI-based experimentation can eliminate some of the manual laboratory positions, but at the same time, will drive the need for bioinformaticians, AI engineers, and computational biologists. Topol, (2019) notes that AI supplements but does not alter human expertise, but reskilling of the workforce is necessary. Data science, machine learning, and systems biology should be incorporated into the biotechnology programs in educational institutions. The key to innovation and ethical management will be interdisciplinary training programmes.

1.6 Conclusion

Artificial intelligence (AI) and biotechnology intersected each other signalling a paradigm shift in biological research and innovation. In protein-structure prediction, drug discovery, genomics and synthetic biology, AI-based predictive modelling of complex biological systems has relegated biotechnology to being more largely driven by empirical experimentation, in favor of computational design. The key benefit of AI integration is that it can identify meaningful patterns of large-dimensional omics data. Machine-learning models are used to improve variant interpretation, molecular-interaction-prediction, and therapeutic prioritization (Libbrecht and Noble, 2015). AI-based molecular design and drug target identification lowers the drug development attrition rate and speeds up the discovery of targets at an early stage (Vamathevan et al., 2019). Deep learning talent like the AlphaFold depicts how the new technology can resolve unresolved biological problems having direct translational applications (Jumper et al., 2021). In addition to efficiency, AI is altering translational research due to the combination of genomic, phenotypic, and clinical data that assist in precision medicine (Topol, 2019). Reports on the development of automated and semi-autonomous experimental systems also indicate a coming together of adaptive, closed-loop biological engineering (King et al., 2009). These systems combine computational predictions and high-throughput validation, which generates the scale and pace of innovation. Nevertheless, responsible governance, interpretability, and equally accessing biotechnology based on AI depend on its long-term success. Within the scope of the integration of AI as a part of the biotechnology value chain, a cross-functional team will be required to provide the sustainable and ethical progression. To conclude, it is important to note that AI is not a simple technological extension of biotechnology, but a radical re-engineering of the mechanism of biological system cognition, design, and transfer to the concrete benefits of society.

References

- [1] Alipanahi, B., Delong, A., Weirauch, M. T., and Frey, B. J. (2015). Predicting the sequence specificities of DNA- and RNA-binding proteins by deep learning. *Nature Biotechnology*, 33(8), 831–838. <https://doi.org/10.1038/nbt.3300>
- [2] Anand, N., and Huang, P. -S. (2018). Generative modeling for protein structures. *Advances in Neural Information Processing Systems*, 31,

- 7494–7505. <https://papers.nips.cc/paper/2018/hash/9eaf4e37b17b9e5e7a3a0a43b2e07b6b-Abstract.html>
- [3] Baek, M., DiMaio, F., Anishchenko, I., Dauparas, J., Ovchinnikov, S., Lee, G.R., Wang, J., Cong, Q., Kinch, L. N., Schaeffer, R. D., and Millán, C. (2021). Accurate prediction of protein structures and interactions using a three-track neural network. *Science*, 373(6557), 871–876. <https://doi.org/10.1126/science.abj8754>
- [4] Barabasi, A. -L., and Oltvai, Z. N. (2004). Network biology: Understanding the cell's functional organization. *Nature Reviews Genetics*, 5(2), 101–113. <https://doi.org/10.1038/nrg1272>
- [5] Barabasi, A. -L., Gulbahce, N., and Loscalzo, J. (2011). Network medicine: A network-based approach to human disease. *Nature Reviews Genetics*, 12(1), 56–68. <https://doi.org/10.1038/nrg2918>
- [6] Bycroft, C., Freeman, C., Petkova, D., Band, G., Elliott, L. T., Sharp, K., Motyer, A., Vukcevic, D., Delaneau, O., O'Connell, J., and Cortes, A. (2018). The UK Biobank resource with deep phenotyping and genomic data. *Nature*, 562(7726), 203–209. <https://doi.org/10.1038/s41586-018-0579-z>
- [7] Chuai, G., Ma, H., Yan, J., et al. (2018). DeepCRISPR: Optimized CRISPR guide RNA design by deep learning. *Genome Biology*, 19(1), 80. <https://doi.org/10.1186/s1059-018-1459-4>
- [8] Ciriello, G., Miller, M. L., Aksoy, B. A., Senbabaoglu, Y., Schultz, N., and Sander, C. (2013). Emerging landscape of oncogenic signatures across human cancers. *Nature Genetics*, 45(10), 1127–1133. <https://doi.org/10.1038/ng.2762>
- [9] Crossa, J., Pérez-Rodríguez, P., Cuevas, J., Montesinos-López, O., Jarquín, D., De Los Campos, G., Burgueño, J., González-Camacho, J. M., Pérez-Elizalde, S., Beyene, Y., and Dreisigacker, S. (2017). Genomic selection in plant breeding. *Trends in Plant Science*, 22(11), 961–975. <https://doi.org/10.1016/j.tplants.2017.08.011>
- [10] Doench, J. G., Fusi, N., Sullender, M., Hegde, M., Vaimberg, E. W., Donovan, K. F., Smith, I., Tothova, Z., Wilen, C., Orchard, R., and Virgin, H. W. (2016). Optimized sgRNA design to maximize activity and minimize off-target effects. *Nature Biotechnology*, 34(2), 184–191. <https://doi.org/10.1038/nbt.3437>
- [11] Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., and Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature*, 542(7639), 115–118. <https://doi.org/10.1038/nature21056>
- [12] Gilmer, J., Schoenholz, S. S., Riley, P. F., Vinyals, O., and Dahl, G. E. (2017). Neural message passing for quantum chemistry. *Proceedings of ICML*. <https://proceedings.mlr.press/v70/gilmer17a.html>

- [13] Gymrek, M., McGuire, A. L., Golan, D., Halperin, E., and Erlich, Y. (2013). Identifying personal genomes by surname inference. *Science*, 339(6117), 321–324. <https://doi.org/10.1126/science.1229566>
- [14] Morselli Gysi, D., Do Valle, Í., Zitnik, M., Ameli, A., Gan, X., Varol, O., Ghiassian, S. D., Patten, J. J., Davey, R. A., Loscalzo, J., and Barabási, A. L. (2021). Network medicine framework for identifying drug repurposing opportunities for COVID-19. *Proceedings of the National Academy of Sciences*, 118(19), e2025581118. <https://doi.org/10.1073/pnas.2025581118>
- [15] Ioannidis, J. P. A. (2005). Why most published research findings are false. *PLoS Medicine*, 2(8), e124. <https://doi.org/10.1371/journal.pmed.0020124>
- [16] Jordan, M. I., and Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, 349(6245), 255–260. <https://doi.org/10.1126/science.aaa8415>
- [17] Jumper, J., Evans, R., Pritzel, A., et al. (2021). Highly accurate protein structure prediction with AlphaFold. *Nature*, 596(7873), 583–589. <https://doi.org/10.1038/s41586-021-03819-2>
- [18] King, R. D., Rowland, J., Oliver, S. G., et al. (2009). The automation of science. *Science*, 324(5923), 85–89. <https://doi.org/10.1126/science.1165620>
- [19] Kircher, M., Witten, D. M., Jain, P., et al. (2014). A general framework for estimating the relative pathogenicity of human genetic variants. *Nature Genetics*, 46(3), 310–315. <https://doi.org/10.1038/ng.2892>
- [20] Kitano, H. (2002). Systems biology: A brief overview. *Science*, 295(5560), 1662–1664. <https://doi.org/10.1126/science.1069492>
- [21] Kumar, N., et al. (2023). Biosecurity in the age of AI-enabled biology. *Nature Biotechnology*, 41, 155–161. <https://doi.org/10.1038/s41587-023-01710-7>
- [22] LeCun, Y., Bengio, Y., and Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436–444. <https://doi.org/10.1038/nature14539>
- [23] Lee, J., Yoon, W., Kim, S., et al. (2020). BioBERT: A pre-trained biomedical language representation model. *Bioinformatics*, 36(4), 1234–1240. <https://doi.org/10.1093/bioinformatics/btz682>
- [24] Libbrecht, M. W., and Noble, W. S. (2015). Machine learning applications in genetics and genomics. *Nature Reviews Genetics*, 16(6), 321–332. <https://doi.org/10.1038/nrg3920>
- [25] Lundberg, S. M., and Lee, S. -I. (2017). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*, 30, 4765–4774. <https://papers.nips.cc/paper/2017/hash/8a20a8621978632d76c43dfd28b67767-Abstract.html>

- [26] Martin, A. R., Kanai, M., Kamatani, Y., et al. (2019). Clinical use of current polygenic risk scores may exacerbate health disparities. *Nature Genetics*, 51(4), 584–591. <https://doi.org/10.1038/s41588-019-0379-x>
- [27] Mason, D. M., Friedensohn, S., Weber, C. R., et al. (2021). Deep learning enables therapeutic antibody optimization. *Nature Biotechnology*, 39(5), 594–602. <https://doi.org/10.1038/s41587-020-0707-8>
- [28] Metzker, M. L. (2010). Sequencing technologies — the next generation. *Nature Reviews Genetics*, 11(1), 31–46. <https://doi.org/10.1038/nrg2626>
- [29] Nielsen, J., and Keasling, J. D. (2016). Engineering cellular metabolism. *Cell*, 164(6), 1185–1197. <https://doi.org/10.1016/j.cell.2016.02.004>
- [30] Nijkamp, E., Ruffolo, J., Weinstein, E., et al. (2023). ProGen2: Exploring the boundaries of protein language models. *Cell Systems*, 14(11), 968–982. <https://doi.org/10.1016/j.cels.2023.01.007>
- [31] O'Brien, M., and Nelson, B. (2020). Synthetic biology and biosecurity: Balancing innovation and risk. *Frontiers in Bioengineering and Biotechnology*, 8, 621. <https://doi.org/10.3389/fbioe.2020.00621>
- [32] Paul, S. M., Mytelka, D. S., Dunwiddie, C. T., et al. (2010). How to improve RandD productivity: The pharmaceutical industry's grand challenge. *Nature Reviews Drug Discovery*, 9(3), 203–214. <https://doi.org/10.1038/nrd3078>
- [33] Raj, A., and Van Oudenaarden, A. (2008). Nature nurture or chance: Stochastic gene expression and its consequences. *Cell*, 135(2), 216–226. <https://doi.org/10.1016/j.cell.2008.09.050>
- [34] Reynisson, B., Alvarez, B., Paul, S., et al. (2020). NetMHCpan-4.1 improved predictions of MHC antigen presentation. *Nucleic Acids Research*, 48(W1), W449–W454. <https://doi.org/10.1093/nar/gkaa379>
- [35] Schwab, K. (2016). The fourth industrial revolution. *Foreign Affairs*, 95(6), 52–57. <https://www.foreignaffairs.com/articles/2015-12-12/fourth-industrial-revolution>
- [36] Subramanian, I., Verma, S., Kumar, S., et al. (2022). Multi-omics data integration, interpretation, and its application. *Bioinformatics and Biology Insights*, 16, 11779322221098740. <https://doi.org/10.1177/11779322221098740>
- [37] Tang, F., Barbacioru, C., Wang, Y., et al. (2009). mRNA-Seq whole-transcriptome analysis of a single cell. *Nature Methods*, 6(5), 377–382. <https://doi.org/10.1038/nmeth.1315>
- [38] Topol, E. J. (2019). High-performance medicine: The convergence of human and artificial intelligence. *Nature Medicine*, 25(1), 44–56. <https://doi.org/10.1038/s41591-018-0300-7>

- [39] U.S. Food and Drug Administration (FDA). (2019). Proposed regulatory framework for modifications to AI/ML-based software as a medical device. <https://www.fda.gov/media/122535/download>
- [40] Vamathevan, J., Clark, D., Czodrowski, P., et al. (2019). Applications of machine learning in drug discovery and development. *Nature Reviews Drug Discovery*, 18(6), 463–477. <https://doi.org/10.1038/s41573-019-0024-5>
- [41] Visscher, P. M., Wray, N. R., Zhang, Q., et al. (2017). 10 years of GWAS discovery: Biology function and translation. *American Journal of Human Genetics*, 101(1), 5–22. <https://doi.org/10.1016/j.ajhg.2017.06.005>
- [42] Walters, W. P., and Murcko, M. (2023). Assessing generative models for molecular design. *Nature Reviews Drug Discovery*, 22, 819–820. <https://doi.org/10.1038/s41573-023-00600-7>
- [43] World Health Organization (WHO). (2023). Ethics and governance of artificial intelligence for health. <https://doi.org/www.who.int/publications/i/item/9789240029200>
- [44] Wrapp, D., Wang, N., Corbett, K. S., et al. (2020). Cryo-EM structure of the SARS-CoV-2 spike. *Science*, 367(6483), 1260–1263. <https://doi.org/10.1126/science.abb2507>
- [45] Zhavoronkov, A., Ivanenkov, Y. A., Aliper, A., et al. (2019). Deep learning enables rapid identification of potent DDR1 kinase inhibitors. *Nature Biotechnology*, 37(9), 1038–1040. <https://doi.org/10.1038/s41587-019-0224-x>
- [46] Zhou, J., and Troyanskaya, O. G. (2015). Predicting effects of noncoding variants with deep learning-based sequence model. *Nature Methods*, 12(10), 931–934. <https://doi.org/10.1038/nmeth.3547>

Chapter 2

INTELLIGENT COMPUTING IN BIOLOGY: ADVANCES AND PERSPECTIVES

Tanvi Bansal

Student, Department of Molecular Biology and Biochemistry, Guru Nanak Dev University, Amritsar, Punjab, India-143005.

Email: tanvibansal1131@gmail.com

Abstract

In recent years, Artificial Intelligence has brought a major shift in the biological sciences by enabling researchers to examine complex data, spot patterns, and predict results. This abstract highlight the recent advances and future perspectives of AI in biological sciences. New developments in integrative biology are being made possible by the growing recognition of the interdependence of human and nonhuman animal health. We discuss how intelligent computing is being used to analyze large datasets. Advances in machine learning have a strong impact on agriculture, planetary health, and genetics. We also highlight challenges for future research, including the need for interpretable models, experimental biology etc. In biology, the progress of intelligent computing is already significantly impacting this field by precisely examining genomics, proteomics and transcriptomics. Through deep learning methods, it offers solutions in gene prediction, diagnoses and personalized medicine. In the future it aims to tackle data quality, ethical issues and model explainability in order to improve healthcare outcomes.

Keywords: Artificial Intelligence, Biological Sciences, Machine Learning, Multiomics, Medical Diagnostics.

2.1 Introduction

Since its early beginnings in 1956 as a field of research and development, AI has evolved and suffered setbacks, until early

in the 21st century when it finally flourished with successful applications in academia and industry. A combination of new methods and availability of powerful computers along with vast collections of data brought large investment and widespread interest in AI (Hassoun et al., 2022). With the growing population it is very difficult to manage our day-to-day lives without using intelligent computing. There are several fields where intelligent computing has become a necessary feature. Recent advances in intelligent computing have been transformative to biological sciences, enabling high-accuracy interpretation of massive biological datasets of genomic, proteomic, and transcriptomic information (Subramanian et al., 2020). Both deep learning (DL) and neural network architectures are employed extensively in gene prediction, diagnostics, protein structure prediction and customized treatment paradigms, with DL-based tools such as AlphaFold in particular completely transforming structural biology with their highly accurate three-dimensional prediction of protein structures, accelerating both drug discovery and biomolecular research (Jumper et al., 2021). Multi-omics datasets combined with ML have also significantly enhanced understanding of cellular heterogeneity, cancer progression and disease mechanisms. Intelligent computing has furthermore supported precision medicine by helping to identify disease associated biomarkers and patient-specific therapeutic response predictions, with XAI currently a burgeoning area of bioinformatics, focused on improving reliability and interpretation of computational models for clinical research and healthcare (Zhou et al., 2023). Systems biology has greatly benefited from intelligent computing applications that enable modeling of complex biological network interactions to a much greater extent than traditional approaches. Additionally, generative AI has become crucial for de novo molecule, sequence, and drug candidate design and the combination of high-performance computing and AI techniques has drastically shortened processing and simulation times for biological data studies (Walters and Murcko, 2020). AI-enabled bioinformatics platforms are also facilitating automation in lab processes, image analysis, and real-time clinical decisions (Bhardwaj et al., 2022). Critical challenges remain however in biological computing with regard to data quality, ethics, costs, and model interpretation. However, integration between AI, cloud computing, big data analytics and biotechnology is anticipated to drive fundamental change within biological sciences

and healthcare across the globe in the coming years with a resulting rise in diagnostics, therapeutics and improved comprehension of the biological world. From healthcare to industry, it can handle multidimensional heterogeneous data. The combination of silicon and cell is now the driving force behind biological discoveries rather than a futuristic trope. Intelligent computing in biology represents the transformative convergence of artificial intelligence, high-performance computing, and the life sciences. Intelligent computing in medical imaging describes technologically advanced methods to receive the response from a real time environment. Traditional manual analysis is no longer sufficient for the “Big Data” generated by modern high-throughput techniques like genome sequencing so it is an important aspect in life sciences (Hassoun et al., 2022). It reduces human error, speeds up research and uncover hidden patterns in data (Bhardwaj et al., 2022). The key dimensions of Intelligent Computing in Biology are:

- **Computational Biology and Bioinformatics:** Applying machine learning (ML) and statistics to the issue of large scale biological and medical data.
- **Bio-inspired Computing:** To develop software which models biological systems like Genetic Algorithms which are based on principles of evolution and Swarm Intelligence based on ant colonies. This is used to solve complex problems like protein folding and DNA sequence alignment.

In this chapter, we will begin with the advancements and application of intelligent computing in biological sciences and talk about perspectives and how it can bring a change in today's era.

2.2 Historical Evolution

In the history of intelligent computing's role in biology (Table 2.1) which began in the 1950's with manual computation to what we have today in which we use AI powered computing to process large scale biological data and which in turn is transforming the fields of drug discovery, systems biology, and structural biology. This area of study is also known as bioinformatics and computational biology (Shi et al., 2024).

Table 2.1: Historical evolution of intelligent computing’s role in biology.

Era	Key Themes	Major Developments	People/Organizations
Pre-1950s: Foundational Concepts	Biological metaphors in computing; Mathematical biology	• 1948: Proposal of genetic search methods. • Early 20th century: Statistical approaches applied to biology (Searls, 2010).	Alan Turing
1950s–1970s: Dawn of Bioinformatics and Neural Networks	Early computational biology; Protein sequencing; Database creation; Algorithm development	• 1952: Morphogenesis modelling using Manchester Mark I. • Early 1960s: Comproteins software. • 1965: Atlas of Protein Sequence and Structure database. • 1970: Needleman–Wunsch global alignment algorithm. • Early 1970s: Formalization of bioinformatics (Shi et al., 2024; Searls, 2010).	Margaret O. Dayhoff; Robert S. Ledley; Paulien Hogeweg; Ben Hesper

Continued on next page

Table 2.1 (continued)

Era	Key Themes	Major Developments	People/Organizations
1980s–1990s: Databases, Sequence Analysis and Expert Systems	Genomic databases; Sequence alignment tools; AI expert systems; DNA computing	• 1980: EMBL nucleotide database. • 1982: GenBank. • 1990: BLAST tool. • 1980s: DENDRAL and MYCIN expert systems. • 1994: DNA computing solves the travelling salesman problem (Shi et al., 2024).	European Molecular Biology Laboratory; National Institutes of Health; Leonard Adleman
2000s–2010s: High-Throughput Data and Machine Learning	Large-scale sequencing; Machine learning; Data integration; Systems biology	• Early 2000s: Completion of the Human Genome Project. • Integration of Support Vector Machines, Random Forests and Hidden Markov Models. • Growth of systems biology modelling (Shi et al., 2024).	Human Genome Project

Continued on next page

Table 2.1 (continued)

Era	Key Themes	Major Developments	People/Organizations
2010s– Present: Deep Learning and AI-Driven Discovery	Deep learning in biology; Protein structure prediction; AI drug discovery; Organoid intelligence	• 2018–2024: AlphaFold breakthroughs. • 2022: First AI-developed drug enters clinical trials. • 2024: Nobel Prize in Chemistry awarded for AlphaFold-related work. • Emergence of organoid intelligence (Shi et al., 2024).	Google DeepMind (AlphaFold)

2.3 Advances In Intelligent Computing Techniques

Biology has undergone a major change due to intelligent computing in the field(s) of artificial intelligence (AI), machine learning (ML) and bio-computing by having the ability to process and analyze large volumes of biological data (Ching et al., 2018). Breakthroughs in this area include AlphaFold, an AI tool for predicting protein structures with greater accuracy; AI drugs developed through drug design, including Halicin (an antibiotic compound used to combat multi-drug resistant bacterial infections); and bio-computing, where live cells, specifically brain organoids, can be used as computers that perform computations at much lower energy costs than supercomputers (Cai et al., 2023). In this chapter, various advanced forms of computation are presented as “foundations” or “pillars” upon which the creation of biological intelligence will be built (Table 2.2). As a result, these computations mark the beginning of the shift from traditional data processing to systems that possess reasoning, perception, etc.

Table 2.2: AI systems with importance in biological research

Advance	Description	Impact
Protein structure prediction (AlphaFold)	Predicts 3D protein shapes from amino acid sequences	Speed up drug design from years to hours.
Precision Medicine	Analyses genomic data for personalized treatments (Ahmed et al., 2020)	Spots disease biomarkers early.
Gene Expression Analysis	AI models predict gene functions and interactions	Accelerates biotech innovations.
Drug- Target Prediction	Forecasts how drugs bind to proteins	Improves drug discovery efficiency.

2.4 Applications Of Intelligent Computing

We use AI, machine learning, and complex algorithms in intelligent computing to put together solutions to very large bio questions from the code in DNA to the development of new drugs. These techs work with huge sets of data which we use to see trends that the human eye may not catch (Nalina et al., 2025, Li et al., 2024).

2.4.1 Genomics and Sequence Analysis

AI has great success in analysis of DNA, RNA, and protein sequences which in turn predicts functions and structures. In the field of large language models which include BERT based models (for instance, TCR-BERT and GeneBERT), we see that they do analysis which includes T cell receptor binding to epitopes, epigenetic issues like DNA methylation, and histone regulation which in turn improves the accuracy in cross species predictions and disease etiologies (Li et al., 2024; Jamialahmadi et al., 2024).

2.4.2 Protein Structure and Drug Discovery

In genomics we see that fine tuning models on large data sets which in turn speeds up gene discovery for personal medicine. Also, we have methods like AlphaFold which does the prediction of the 3D structure of proteins from their sequence which in turn reduces the time to design a new drug from years to days. LLMs and deep learning are creating new proteins and molecules, we see AI designed drugs which will enter clinical trials that through virtual screening of drug target interactions will report back 60% faster in to development (Li et al., 2024; Jamialahmadi et al., 2024; Jiang et al., 2025).

2.4.3 Precision and Personalized Medicine

AI is developing “digital twins” of patients that use genetic, wearable, and health info to predict disease outcomes and personal care. Brain computer interfaces like Neuralink are allowing paralyzed patients to turn thought into action, and wearables are putting out disease based on bio metrics which in turn is changing medicine from a reactive to a preventive field. In cancer research, random forests have identified gene signatures (for instance a 6 gene panel for breast cancer) which are used in early diagnosis and prognosis (Nalina et al., 2025).

2.4.4 Omics Data Integration

Multi-omics (genomics, proteomics, and metabolomics) generates petabytes of data which AI integrates via a hybrid model of neural networks, transformers, and cloud computing. In DeepCORE and other deep learning software we see the visualization of the interaction between genetic and epigenetic elements and at the same time RNNs are used to analyze dynamic biological networks from expression data which in turn is used in systems biology research (Li et al., 2024; Jamialahmadi et al., 2024).

2.4.5 Synthetic Biology and Bioengineering

Also, AI has a role in what we may call “algorithms driven” design of new life forms, that which optimizes genetic circuits and which also does better in predicting the performance of synthetic organisms. By 2026, machine learning will have greatly improved RandD in biotech companies. Efforts are being put to develop customized microbes

for biofuel or pharmaceutical production which will also outperform what we do today with human approaches (Nalina et al., 2025).

2.5 Challenges And Limitations

Because of the complexities of biology, there are numerous obstacles in implementing AI in bioinformatics; even though there are numerous examples of strong AI like AlphaFold, these challenges will continue to present difficulties as we develop new ways to apply AI in biotechnology.

2.5.1 Data Quality Issues

Omics (genomic and proteomic) biological data are noisy, contain batch effects and missing values, and can vary from laboratory or population center to laboratory or population center. Using this data in AI models can bias the models if they are trained using imbalanced demographic or protocol data; thus, when the models are applied to representative data, they may demonstrate poor performance. Human generated pre-processed data can provide more insight than AI generated pre-processed data and use of multiple omics data will introduce additional variability (Jiang et al., 2025).

2.5.2 Reproducibility Problems

Reproducing AI results requires identical code, library versions, hardware, hyperparameters, and random seeds, which is more difficult than wet-lab replications. There is also an issue of not having standardized pipelines for training which in turn makes results hard to replicate across studies. Also, AI models do not do a good job of generalizing to new populations outside of the trained groups which is a result of their poor performance in new conditions (Vo et al., 2026).

2.5.3 Interpretability Gaps

Deep learning is a “closed box” which does not reveal how it comes to its predictions that results in a loss of confidence in clinical settings. Also, it is hard to interpret the results which are very important for diagnosis and drug approval (Vo et al., 2026).

2.5.4 Data Scarcity and Privacy

There is a lot of raw omics data out there but we are lacking in terms of labeled and processed data for training as AI models do in fact perform better on what experts put out rather than what is presented in unfiltered form. Also, we must note that patient data is very private which makes it hard to share between parties due to GDPR and HIPAA (Wu and Xie, 2024).

2.6 Conclusion

Intelligent computing is at the core of what we see in modern biology today. We have at our disposal tools which are very good at looking at large genomic, proteomic, transcriptomic, and multi-omics data sets which in turn are helping us to see patterns and to determine relationships which till now have gone unseen. We have seen great progress in deep learning and large language models used for sequence analysis, protein structure prediction tools like AlphaFold, and AI in drug discovery which has in turn sped up the processes from hypothesis formulation to molecule design and translation research. These breakthroughs have brought about real results in terms of better prediction of protein structures, identification of biomarkers, personalizing medicine for patients and in the automation of lab and image analysis. At the same time, it is important to note that we still have some major issues to work out.

Biotech and medical data are of poor quality and variable which in turn means we have scarce labeled training sets, also we see that privacy issues and regulation play a big role in which we are unable to share data. Also, we see that reproduction of AI results is an issue and that many of the best models we have are a black box which do not translate well into clinical practice. To improve on this, we need to see more curating and standardization of data, we need better methods which are at the same time interpretable and robust, we also need better integration between what computation is putting out and what we see in the lab and finally we need to come up with better ways to share very private data. Looking forward we see that explainable AI which is tailored for bio medical issues is a growth area, we also see hybrid models which put together mechanistic knowledge with data driven algorithms and federated learning which protects privacy while still allowing for wide data collection and we may even see bio

hybrid computing. These are the directions that may help to achieve high performance at the same time as also providing the transparency and reliability that clinicians and patients require.

In a nutshell, we see that smart computing has in fact transformed the way in which we study biology and we also see that it has the very real chance to improve diagnosis, treatment and our large-scale understanding of living systems. We will see that which of this promise is realized is dependent upon careful validation, open discussion of methods and issues at hand, and close work between computational researchers, clinical professionals, ethicists and experimental biologists which is to say that the advances do in fact benefit all people in a safe and fair way.

References

- [1] Ahmed, Z., Mohamed, K., Zeeshan, S., and Dong, X. (2020). Artificial intelligence with multi-functional machine learning platform development for better healthcare and precision medicine. *Database: the journal of biological databases and curation*, baaa010. <https://doi.org/10.1093/database/baaa010>
- [2] Bhardwaj, A., Kishore, S., and Pandey, D. K. (2022). Artificial Intelligence in Biological Sciences. *Life*, 12, 1430. <https://doi.org/10.3390/life12091430>
- [3] Bhardwaj, P., Gupta, P., Guhan, T., and Srinivasan, K. (2022). Early Diagnosis of Retinal Blood Vessel Damage via Deep Learning-Powered Collective Intelligence Models. *Computational and mathematical methods in medicine*, 2022, 3571364. <https://doi.org/10.1155/2022/3571364>
- [4] Cai, H., Ao, Z., Tian, C. et al. (2023). Brain organoid reservoir computing for artificial intelligence. *Nature Electronics*, 6, 1032–1039 <https://doi.org/10.1038/s41928-023-01069-w>
- [5] Ching, T., Himmelstein, D. S., Beaulieu-Jones, B. K., Kalinin, A. A., Do, B. T., Way, G. P., Ferrero, E., Agapow, P. M., Zietz, M., Hoffman, M. M., Xie, W., Rosen, G. L., Lengerich, B. J., Israeli, J., Lanchantin, J., Woloszynek, S., Carpenter, A. E., Shrikumar, A., Xu, J., Cofer, E. M., ... Greene, C. S. (2018). Opportunities and obstacles for deep learning in biology and medicine. *Journal of the Royal Society, Interface*, 15(141), 20170387. <https://doi.org/10.1098/rsif.2017.0387>
- [6] Hassoun, S., Jefferson, F., Shi, X., Stucky, B., Wang, J., and Rosa, E. (2022). Artificial Intelligence for Biology. *Integrative and comparative biology*, 61(6), 2267–2275. <https://doi.org/10.1093/icb/icab188>
- [7] Jamialahmadi, H., Khalili-Tanha, G., Nazari, E., and Rezaei-Tavirani, M. (2024). Artificial intelligence and bioinformatics: a

- journey from traditional techniques to smart approaches. *Gastroenterology and hepatology from bed to bench*, 17(3), 241–252. <https://doi.org/10.22037/ghfbb.v17i3.2977>
- [8] Jiang, J., Li, Y., Cao, S., Shan, Y., Liu, Y., Fei, T., Yu, Y., Feng, Y., Li, Y., Li, Y., and Yuan, J. (2025). Artificial intelligence in bioinformatics: a survey. *Briefings in bioinformatics*, 26(6), bbaf576. <https://doi.org/10.1093/bib/bbaf576>
 - [9] Jumper, J., Evans, R., Pritzel, A., Green, T., Figurnov, M., Ronneberger, O., Tunyasuvunakool, K., Bates, R., Žídek, A., Potapenko, A., Bridgland, A., Meyer, C., Kohl, S. A. A., Ballard, A. J., Cowie, A., Romera-Paredes, B., Nikolov, S., Jain, R., Adler, J., Back, T., et al. (2021). Highly accurate protein structure prediction with AlphaFold. *Nature*, 596(7873), 583–589. <https://doi.org/10.1038/s41586-021-03819-2>
 - [10] Nalina, V., Prabhu, D., Sahayarayan, J. J., Vidhyavathi, R. (2025). Advancements in AI for Computational Biology and Bioinformatics: A Comprehensive Review. In: Mandal, S. (eds) *Artificial Intelligence (AI) in Cell and Genetic Engineering. Methods in Molecular Biology*, 2952. Humana, New York, NY. https://doi.org/10.1007/978-1-0716-4690-8_6
 - [11] Li, F., Liu, L., Wang, K., Liu, X., and Zhao, Z. (2024). Intelligent biology and medicine: Accelerating innovative computational approaches. *Computational and structural biotechnology journal*, 27, 32–34. <https://doi.org/10.1016/j.csbj.2024.11.044>
 - [12] Searls D. B. (2010). The roots of bioinformatics. *PLoS computational biology*, 6(6), e1000809. <https://doi.org/10.1371/journal.pcbi.1000809>
 - [13] Shi, L., Wang, M., and Wang, X. J. (2024). Application of artificial intelligence in life science: Historical review and future perspectives. *Fundamental research*, 6(1), 20–27. <https://doi.org/10.1016/j.fmre.2024.10.014>
 - [14] Subramanian, I., Verma, S., Kumar, S., Jere, A., and Anamika, K. (2020). Multi-omics Data Integration, Interpretation, and Its Application. *Bioinformatics and biology insights*, 14, 1177932219899051. <https://doi.org/10.1177/1177932219899051>
 - [15] Vo, T. H., Le, N. Q. K. (2026). Toward trustworthy artificial intelligence in multi-omics: a review of reproducibility, stability, and interpretability, *Briefings in Bioinformatics*, 27(3), 227. <https://doi.org/10.1093/bib/bbag227>
 - [16] Walters, W. P., and Murcko, M. (2020). Assessing the impact of generative AI on medicinal chemistry. *Nature biotechnology*, 38(2), 143–145. <https://doi.org/10.1038/s41587-020-0418-2>
 - [17] Wu, Y., and Xie, L. (2024). AI-driven multi-omics integration for multi-scale predictive modeling of causal genotype-environment-phenotype relationships. *arXiv preprint arXiv:2407.06405*.

-
- [18] Zhou, Z., Hu, M., Salcedo, M., Gravel, N., Yeung, W., Venkat, A., et al. (2023). XAI meets biology: a comprehensive review of explainable AI in bioinformatics applications. *arXiv preprint arXiv:2312.06082*.

NOTES

This image shows a single sheet of white paper with horizontal ruling lines. The lines are evenly spaced and run across the width of the page. There are no margins, text, or other markings on the paper.

Chapter 3

GUARDIANS OF BIODIVERSITY: ARTIFICIAL INTELLIGENCE REVOLUTIONIZING ANIMAL CONSERVATION

Ramanpreet Kaur* & Monita Dhiman

Assistant Professor, Department of Zoology, Khalsa College for Women, Civil Lines, Ludhiana, Punjab, India-141001.

*Email: ramanpreet0062@yahoo.com

Abstract

The threat of rapid loss of biodiversity due to habitat destruction, climate change, pollution, overexploitation and wildlife trade poses a significant threat to animal conservation. Although necessary, the conventional methods used for animal conservation sometimes become ineffective in dealing with complexity and urgency of the threats. Recently, AI (Artificial Intelligence) has emerged as a potential tool in the field of conservation biology, which provides new solutions for the monitoring, conservation and management of animal populations and ecosystems. This chapter explores the increasing application of AI in animal conservation. The applications of AI in monitoring of wildlife, identification of species, evaluation of animal habitat, anti-poaching efforts, monitoring of disease and conservation policy formulation are explored. This chapter presents an overview of the applicability of AI-powered technology in conservation activities like tracking endangered species, handling vast data sets and improving conservation outcomes. In addition, this chapter presents an overview of the ethical implications of AI technology in conservation activities and the challenges facing AI technology in conservation. Finally, the future directions and research opportunities are presented, with a special emphasis on the application of AI in improving adaptive management practices, conserving effective conservation policies

and facilitating a harmonious coexistence between humans and animals. AI, by successfully filling the gap between technology and biology, promises a bright future for more efficient, data driven and robust animal conservation in the Anthropocene epoch.

Keywords: Conservation Biology, Monitoring, Biodiversity Protection, Remote Sensing, Bioacoustics

3.1 Introduction

Biodiversity is not just a pleasant addition to nature; it is what gives ecosystems depth and allows us to survive, adapt to suffering and continue running at full speed (Chen et al., 2020). Animals are an essential part of nature's equilibrium to support the survival of all living organisms through acts like pollination and seed dispersal, which spread throughout diverse ecosystems (Krenn et al., 2022). Human influence is reducing biodiversity at an alarming rate globally, thereby endangering animal species (Binley et al., 2024). The current biodiversity crisis is due to factors like habitat loss, climate change, pollution, depletion of natural resources, wildlife poaching and increased extinction rate (García-Roselló et al., 2023). Conservation strategies like creating protected areas, conducting species counts and enforcement have helped us make some positive progress, but what we face today cannot be contained by such means (Kulkarni and Di Minin, 2023). The ecosystems stretch thousands of miles but resources cannot be extended endlessly and environmental change is occurring at an unprecedented rate. What we need now is new and effective measures to match the speed at which we face this crisis.

Artificial intelligence allows for the development of fresh mechanisms through which wildlife resistance can be strengthened. This is due to its capacity for quickly rummaging through massive intricate data sets in the blink of an eye (Krenn et al., 2022). Artificial intelligence, coupled with the life sciences, represents a brand-new period in the latter's history, one that has historically placed it at the upper echelon of scientific exploration (Binley et al., 2024). Biodiversity depletion around the world has been recognized as the sixth mass extermination caused by human activities that force species towards extinction. For instance, global statistics indicate a decline of animal populations worldwide, including land, water and sea (Spelda and Stritecky, 2020). Deforestation,

urbanization, agriculture and development continue to destroy wildlife habitats, leaving fewer and fewer places for wildlife to live. Rising temperatures continue to alter ecosystems, affecting the regions and areas conducive to large populations of wildlife (Ripple et al., 2017). In addition to climate change, other human activities such as pollution and overexploitation of natural resources continue to contribute to habitat shrinkage. Conventional approaches to conservation studies often depend heavily on availability of manpower over large fieldwork areas (Sutherland et al., 2024). The approaches are important, as they provide critical information for general ecological understanding; however, they might be restricted by funding and availability or might not provide the most recent information necessary for decision-making purposes (Krenn et al., 2022). With the availability of such vast information about ecology, conservation needs technology as opposed to conventional approaches (Kulkarni and Di Minin, 2023).

The gaps in the field of conservation, in relation to precision, efficiency and scalability, can be filled by the introduction of the use of AI technology (Sutherland et al., 2024). The use of artificial intelligence is based on the intelligence of the human mind, where learning, recognizing, categorizing and making decisions can be carried out in an efficient manner. Within the realms of the biological field, the use of AI as a tool for the analysis of complex data can be carried out in an efficient manner (Spelda and Stritecky, 2020). In the context of conservation biology, the use of artificial intelligence can be employed for the identification of various species by the use of images, audio, the tracking of the routes of animals, the creation of habitat models where the conserved species have a high probability of surviving, as well as the forecasting of poaching (Ripple et al., 2017). The use of artificial intelligence, along with disciplines such as ecology, wildlife biology and environmental science can lead to the broad range of new conservation routes (García-Roselló et al., 2023). The use of AI is likely to reduce the time taken to process the data, along with the use of increased power in decision-making.

This chapter will discuss how Artificial Intelligence is becoming even more central to animal conservation within the wider field of biology. It will be a wide-ranging review of how AI tools address the fundamental problems facing animal conservation, from tracking

and identifying species to habitats, poaching, diseases and informing conservation policies. Its concrete goals are:

- to identify the key AI techniques and tools used by conservationists;
- to illustrate the role of AI in tracking endangered species and dealing with large data sets;
- to explore the ethical, social and technological challenges of bringing AI into conservation work;
- to identify possible future avenues for applying AI technologies to support adaptive management and policy-making;
- to highlight the importance of AI in enhancing the sustainability of the relationship between human kind and the animal kingdom.

Through the combination of technology-based innovation with biological knowledge, the chapter demonstrates the potential of AI in enhancing the effectiveness of conservation in the Anthropocene era and preparing a new and more inclusive strategy of protection for animal life in a constantly changing world (Binley et al., 2024).

3.2 Foundations Of Artificial Intelligence

At its core, “Artificial Intelligence” is an array of computational techniques for computers to execute the type of activities commonly referred to as requiring human “smarts,” or learning from experience, discerning patterns, consuming complex information, making decisions in the presence of uncertainty and learning from changing situations (Kulkarni and Di Minin, 2023). Data, computers and computing techniques are constantly being improved and AI crops up everywhere from conservation biology to environmental science. It is rather useful, therefore, to have a basic understanding of what AI is prior to learning of its key role in the study of wildlife and its conservation (Spelda and Stritecky, 2020). AI is, quite simply, “a computer technology for learning, reasoning, perceiving and problem-solving by mimicking human intelligence.” while other software is simply capable of processing information along a straight line (Chen et al., 2020). The key core concepts of AI include:

a) Learning: AI has an ability to learn from data and get better over time. In conservation biology, this means an AI will be able to

automatically classify species, identify animal behaviour and predict species trends from the data collected.

b) Reasoning and Decision Making: For the case of artificial intelligence, rules, probability and optimization are used to guide decisions. For animal conservation, the most common applications include the assessment of risks, the habitats to be protected and the allocation of resources (Ripple et al., 2017).

c) Perception: Perception involves the interpretation of information picked up through senses such as imagery, sounds and spatial information. For instance, artificial intelligence, as it relates to conservation, helps with camera traps, bioacoustics, drones and satellite imagery analysis (Kulkarni and Di Minin, 2023).

d) Adaptability: Having AI systems adapt to different situations when there is a change in environment or new data is introduced can be important. For example, this might be useful in changing ecosystems faced with effects such as climate change, changes in land use and persistent human activities (Gill, 2019). A practical perspective on AI comes in two main categories:

Narrow AI: An AI capable of carrying out certain tasks such as image recognition and sound identification.

General AI: An AI system engineered to have human-like intelligence, which is currently theoretical. Current conservation applications involve only narrow AI.

3.2.1 Machine Learning, Deep Learning and Neural Networks

Machine learning is the core of what we mean by the metaphor of "artificial intelligence" both physically and metaphorically. Machine learning is the ability of machines to learn and predict things without being specifically programmed for (Binley et al., 2024). Machine learning really excels in conservation biology when handling complex data with minimal tweaking (Gill, 2019). Looking at ML in general terms, there are three types of machine learning:

a) Supervised Learning: It is trained using labelled data to perform tasks such as identifying animals from sounds or images.

b) Unsupervised Learning: This type of learning allows us to recognize patterns within given habitats or behaviours.

c) Reinforcement Learning: This is learning with feedback on the outcome of one's action; it is mostly useful in planning routes in conservation work. All the above approaches reduce the work involved in the field, save on the time taken and make the whole process more efficient in conservation (Krenn et al., 2022).

Deep learning has remained a significant pillar of machine learning, particularly when it comes to dealing with extremely complex patterns that tend to exist within huge sets of data (Chen et al., 2020). With its impressive ability to deal effectively with high-dimensional inputs like images, videos and audio signals, new possibilities of interest to conservationists are emerging out of this development, which was hard to imagine before (Sutherland et al., 2024). With deep learning techniques, new avenues that have been unlocked include:

- Auto-sorting camera trap photographs
- Animal vocalization detection using bioacoustics
- Oversight of marine environment using underwater pictures and identification of animals using their individual characteristics

Artificial neural networks are computing systems which, in a basic sense, are a mimic of the workings of the human brain (Ripple et al., 2017). They consist of a number of units connected in layers, through which information passes and patterns are learned from the data.

In conservation biology, some basic neural network architectures tend to dominate the literature:

- Convolutional Neural Networks (CNNs) for images and videos
- Recurrent Neural Networks (RNNs) for data in sequences
- Long Short-Term Memory (LSTM) networks for modeling time-dependent ecological processes

These tools can also be useful in detecting unexpected patterns as well as enhancing the precision of predictive decisions. Using AI in the biological and environmental sciences represents a profound shift in the manner with which we tend to tackle the complex systems present in nature (Ripple et al., 2017). It is worth noting that the data involved

in the biological sciences is usually complex, multi-dimensional, as well as incomplete.

In ecology and conservation biology, AI is a valuable assistant in a range of key roles. It charts where species occur and monitors, how their populations change over time, models the response of ecosystems to a heating planet, assesses the quality of habitats and monitors land-use changes along with the spread of invasive species and diseases (Spelda and Stritecky, 2020). As environmental science becomes more dependent on AI, we can make sense of satellite images, outputs from climate models and sensor data in ways that bring out ecosystem patterns across great areas and long periods of time, well beyond what was available to us in the past (Jiang et al., 2017). AI also braids together various streams of information-ecological data, climate signals and socio-economic context so we can develop a comprehensive view of conservation challenges (Kulkarni and Di Minin, 2023). When computational science combines with ecology, zoology, environmental science and policy, AI bolsters better inter-disciplinary collaboration, evidence-based decisions, adaptive management and effective conservation strategies (Xu et al., 2023). AI contributes significantly to animal conservation by enabling us to respond before problems compound, raising the accuracy of our detection, forecasting and refinement of interventions. As human impacts escalate in the Anthropocene, AI is coming to be regarded as central to progress in biological and conservation strategies (Binley et al., 2024).

3.3 Applications of AI In Wildlife Monitoring

Camera traps make it possible to monitor and analyse wildlife without any or little human involvement through images and videos taken automatically. The problem, however, arises when the camera traps are many and the data, although necessary, is extremely large (García-Roselló et al., 2023). This is where artificial intelligence comes in, especially in computer vision and machine learning. The three concepts make it possible to make sense of the large amount of data gathered. Computer vision, together with convolutional neural networks, assists camera traps in automatically detecting animals within images and differentiating them from their background, as well as identifying the types of animals they are looking at (Ferraro

et al., 2019). Computer vision basically assists in processing images much quicker and more efficiently than a human ever could.

The AI-trap systems come with obvious advantages. They sort and filter images easily, recognize multiple species with nuanced accuracy and are capable of efficiently detecting rare and elusive species, including nocturnal ones. This avoids human error and observational bias (Xu et al., 2023). But these systems not only recognize known species but are capable of recognizing individuals by identifiable marks and features, including stripes, spots and scars, thus monitoring endangered species without resorting to an invasive method.

3.3.1 Species Identification and Population Estimation

Determining the identification of a given species and making an estimate of the population size constitute a crucial exercise when evaluating some aspects of a particular species and developing a strategy on how to effectively manage a habitat (García-Roselló et al., 2023). Of late, a significant amount of work relating to the identification of a species and interpreting ecological data has been automated thanks to recent developments and AI.

Machine learning and deep learning techniques are used to identify species based on:

- Camera trap photos and videos
- Bioacoustic recordings (animal calls and sounds)
- Aerial and satellite images

The AI system would help alleviate some of the pressure placed on taxonomists by automating the way we recognize things in the world, particularly in mixed environments and hotspots where many creatures are packed into a small space and look similar to one another (Spelda and Stritecky, 2020). For human populations, there are a number of important contributions that AI can make:

- automatically counting people in photos and videos
- using capture-recapture techniques involving recognition of individuals
- estimating density using spatial modeling and predictive algorithms

With the assistance of ecological models, artificial intelligence is also assisting conservationists in carrying out precise numerical calculations to identify declining species, monitor the success of conservation activities and prioritize the conservation of some species instead of others (Chen et al., 2020).

3.3.2 Tracking Animal Movement and Behaviour

The comprehension of animal movements and behaviour is critical for the maintenance of healthy ecosystems and the protection of the lives of the animals in those ecosystems (García-Roselló et al., 2023). Thanks to the power of AI technology, it is easy to track patterns of movements and behaviour based on data from GPS collars, bio-tracking technology and drones.

- Machine learning analyzes movement data
- To map migration routes and seasonal shifts
- Predicting how animals would react according to the environmental changes
- Identify hotspots where the possibility of interaction between humans and animals is higher.

Artificial intelligence is transforming the way we analyse behavioural patterns through the application of video and audio data (Gill, 2019). Through the application of artificial intelligence using deep learning algorithms, we are able to identify a variety of actions that animals are undertaking. The toolkit is vast and we are able to attain extended periods of observing animals through the application of AI. The impact of AI on the analysis of bird movements is felt through the following ways:

- Influencing the pattern of wildlife corridors
- guiding the management of protected areas
- assessing potential effects of infrastructure projects

It is, however, through providing detailed information about how animals interact with their environment that AI can be used for making informed decisions on wildlife management (Binley et al., 2024).

3.4 AI In Habitat Assessment and Ecosystem Management

Having said that, one of the most significant boosts to the evaluation of habitats and ecosystems generally has been the advent of artificial intelligence technology. AI technology is capable of processing massive spatial and environmental data at speeds and accuracies unimaginable even in recent times (Chen et al., 2020). As the importance of the health and accessibility of animal habitats is of critical value in the very survival of animals, AI technology offers valuable insights on how the very landscapes in our world are changing and how this reflects on our very own global biodiversity (García-Roselló et al., 2023).

3.4.1 Remote Sensing and Satellite-Based Monitoring

Remote sensing and satellite monitoring form the foundation upon which contemporary conservation biology is conducted, and this phenomenon has just found a new, consistent ally in the form of artificial intelligence (Sutherland et al., 2024). The satellite, meanwhile, continues to beam information from vast areas, quite literally out of reach and transmit it in a steady stream of information (Spelda and Stritecky, 2020). It analyses them quickly as they are rich in information, and it provides conservationists with timely information regarding various ecosystems, habitats and environments within them. For instance, satellite imaging may help scientists analyse multispectral images and gauge information regarding environments, including habitats, lands, vegetations, water, and the extent of fragmentation and areas of habitat.

3.4.2 Habitat Mapping and Land-Use Change Detection

If we want to understand where exactly the habitats are, as well as their position in the whole ecosystem, it is all dependent on proper habitat mapping. Thus, through the use of artificial intelligence, it is easier to accurately identify these ecosystems through satellite imaging, drone shots and pictures taken from the air (García-Roselló et al., 2023). For instance, through deep learning, we can easily distinguish between forests, wetlands, grasslands, agricultural activities, built-up areas and so on (Xu et al., 2023). The ability of artificial intelligence to recognize changes in ecosystems

is extremely significant to present and future conservationists, particularly when we are concerned with recognizing changes in these natural ecosystems, which have been affected by deforestation, vanishing wetlands, increased urbanization, agricultural activities and so forth (Binley et al., 2024).

3.4.3 Predicting Habitat Suitability under Climate Change

A changing climate, with warmer or colder days, varying rainfall, etc., affects the habitat in all sorts of ways, eventually impacting where the species can live. There are various ways to get an idea of what the future might look like in any given habitat. One of these ways is through artificial intelligence (Ferraro et al., 2019). If we can study where different species tend to exist, it would be easier to create a future picture of where the particular species would be. This would allow conservationists to, therefore, get a jumpstart on things instead of simply reacting (Gill, 2019). This can involve actions that can be taken, like helping the species migrate to other areas or creating safe havens so that there can be an adaptation to the changing climate.

3.5 Combating Wildlife Crime and Poaching Using Artificial Intelligence

The issue of wildlife crime, as well as poaching, remains a constant threat to biodiversity, with typical targets being endangered species like elephants, rhinos, tigers and pangolin (Xu et al., 2023). However, with traditional methods of controlling poaching, which have remained reactive and human-based, proving insufficient, artificial intelligence has become a new normal that will continue to provide effective solutions to address poaching proactively, moving away from reactive approaches that have thus far been ineffective (Sutherland et al., 2024).

3.5.1 Predictive Policing and Poaching Risk Models

Modern techniques of predictive policing are being employed by making use of AI systems to get a glimpse of future poaching activities, which might actually occur in a particular region of interest (Xu et al., 2023). These systems scan through previously identified poaching activities, the movements of the animals, environmental conditions, routes via which the wild game is easily accessible, as well as the

socio-economic conditions of the areas of interest (Ferraro et al., 2019). These AI systems are helping police forces detect poaching activities by making use of machine learning to identify space-time patterns, thereby reducing the pace of poaching activities significantly.

3.5.2 Drone Surveillance and Smart Patrol Systems

The integration of artificial intelligence and drone technology has revolutionized the monitoring of our wildlife and patrols. Today, we have drones that use artificial intelligence, possess thermal imaging, infrared and sharp vision to monitor hard-to-reach areas, even in poor lighting conditions and unfavourable weather (García-Roselló et al., 2023). They can supervise and monitor our wildlife in real time and the computer vision can quickly pick up abnormal human movements, vehicles and animal movements, directing the concerned agencies to the source of the disturbance immediately (Spelda and Stritecky, 2020). Patrolling systems, too, have been upgraded to ensure that our conservation rangers are better protected through the use of GPS, data exchange and the optimization of routes, making our conservation efforts not only affordable and efficient but also sustainable (Binley et al., 2024).

3.5.3 AI-Assisted Law Enforcement and Conservation Planning

In this regard, artificial intelligence enhances the capacity of enforcing the law related to wildlife beyond physical patrols by intensifying the analysis of intelligence gathered, prioritization of the gathered data, and planning (Jiang et al., 2017). Artificial intelligence helps to better understand the patterns surrounding the sale and trafficking of wildlife by sifting through patterns related to seizure data, travel patterns, online stores, and social media activities (Ferraro et al., 2019). In addition, artificial intelligence helps to conduct more evidential activities related to the conservation of the environment by highlighting the areas to look into for better protection, the level of efficiency in enforcing the law related to the protection of the environment and support for informed decisions based on data collected. All these results in a better linkage between technology and the law to support the enhanced capability to reduce wildlife crime (Chen et al., 2020).

3.6 Artificial Intelligence In Disease Surveillance And One Health Approaches

With the emergence of infectious diseases, we can now see the extent to which complex the relationship is between different groups within our ecosystem (García-Roselló et al., 2023). As we witness dwindling habitats, unusual changes in climate and as humans interact more with animals, we increase the odds of a crossover happening, but we already use artificial intelligence to detect diseases more accurately and improve our approach known as one health, combining animal health, human health and environmental health (Xu et al., 2023).

3.6.1 Monitoring Wildlife Diseases and Zoonotic Risks

Artificial intelligence is increasingly being employed to keep tabs on the health of wildlife and to detect illness in animal groups. This machine learning-based detection tool reviews the data collected by cameras placed in areas where animals are photographed in their natural habitat (Spelda and Stritecky, 2020). By identifying unusual behaviours or activities, the tool may be able to detect early warning symptoms of illness. This technology is also helpful in identifying how different viruses, including corona viruses, avian flu and Ebolamay be spreading.

3.6.2 AI-Based Early Warning Systems

Early warning systems that are AI-driven provide an indication of where the diseases can appear or propagate. These systems combine epidemiological data, environment, climate and migrations of susceptible organisms to predict diseases before they get out of hand (Gill, 2019). Therefore, AI can estimate the rate at which certain diseases can propagate, indicating where they are likely to manifest. This can be controlled by acting on that prediction (Jiang et al., 2017).

3.6.3 Implications for Animal and Human Health

The various applications of the use of AI technology in tracking diseases include animal and human health and have a ripple effect on many other aspects of health and environmental elements (Sutherland et al., 2024). Watching over animal diseases is a step toward ensuring the health of endangered species and reducing deaths resulting from disease conditions (Xu et al., 2023). Concurrently,

using AI to get a glimpse of animal-human disease threats heightens the alertness and preparedness of the health of the human population to dangers that might result from the spread of disease from animals to humans within the intricate nature of the relationship between humans, animals, and the environment (Ferraro et al., 2019). As a result of the One Health movement, AI is improving itself by encouraging more collaboration and data-sharing between animal, environment and conservation advocates.

3.7 Artificial Intelligence and Conservation Genetics

Conservation genetics can provide important insights on whether or not a population is sustainable, how it will evolve over time, and what the long-term possibilities are for its species (Spelda and Stritecky, 2020). Lately, artificial intelligence has helped advance genetics studies, particularly in terms of allowing us to analyze massive complex genetic data faster and better using AI technologies.

3.7.1 AI in Genomic and eDNA Analysis

Genomic data is pouring into modern conservation genetics—from whole-genome sequencing to metabarcoding and environmental DNA tests (Xu et al., 2023). Computers, fuelled by artificial intelligence, begin to parse this flood: automating sequence alignments, uncoveries and species identification (Binley et al., 2024). Using machine learning to find rare or hidden species in environmental DNA gathered from water, soil, or air samples—even when they are present at minuscule levels—is possible. AI-driven genomic tools accelerate a workflow while increasing detection rates and push conservation genetics toward speed and affordability.

3.7.2 Identifying Genetic Diversity and Population Structure

Genetic diversity is an essential factor for a species to sustain itself in a changing environment with varied pressures from infections. In this respect, AI plays an important role in understanding the overall genetic composition of any population (Xu et al., 2023). It helps in understanding population structure, gene flow, inbreeding and bottlenecks through marker-assisted analysis. In addition, deep learning helps in identifying complex patterns in data.

3.7.3 Supporting Species Recovery and Breeding Programs

Artificial intelligence is already playing a crucial role in species recovery and captive-breeding programs. AI reduces inbreeding and increases genetic diversity through the application of its choice of potential mates (Xu et al., 2023). Predictive models using AI can forecast how genes would change according to different management scenarios; that informs the conservation actions to be followed (Ripple et al., 2017). For reintroduction, AI enables the selection of promising release sites and post-release survival. Combining genetic insights with ecological and population information, AI has achieved better output in conservation breeding and species restoration.

3.8 Case Studies of AI-Driven Conservation Success

This may be observed with regard to the effect of AI on protecting our natural resources by examining some actual case studies. There have been several examples throughout the world regarding how AI helps improve our natural resources management.

3.8.1 Protecting Endangered Species with AI

Artificial Intelligence in the conservation of endangered species: AI is significantly contributing to the survival of endangered animals such as tigers, elephants, snow leopards and great apes, among others, using intelligent camera and sound detector technology (Binley et al., 2024). This enhances the speed of species identification and analysis by reducing the time taken to do so. Predictive analytics in AI helps to prevent poaching by identifying threat areas and directing patrolling activities to areas of need. This is how AI is assisting in the survival of endangered species (Gill, 2019).

3.8.2 AI in Marine and Terrestrial Conservation

In the ocean, AI helps observe coral reefs, trace the migration of whales, and prevent unlawful fishing practices through satellite pictures (Sutherland et al., 2024). On dry land, AI helps with forest and wetland preservation and can restart grasslands through habitat maps and species distribution models (Xu et al., 2023). The versatility of applications of AI on earth and in oceans explains its association with conservation biology.

3.8.3 Lessons Learned from Global Conservation Projects

Global AI-based conservation initiatives emphasize the importance of interdisciplinarity, data quality, and involvement of local stakeholders. Winsome and successful conservation initiatives generally combine AI approaches with ecological sciences and community engagement (Kulkarni and Di Minin, 2023). As deduced from these case studies, although AI enhances efficiency and accuracy in conservation, it should not entirely displace the conventional approaches and traditional ecologic knowledge (Ripple et al., 2017).

3.9 Ethical, Social and Technical Challenges

The opportunity for AI in the context of conservation is obvious, and it also presents ethical, societal and technical challenges that need to be tackled thoughtfully.

3.9.1 Data Bias, Transparency and Reliability

The credibility of AI is heavily dependent on data quality used during training. Therefore, it is important to be transparent about the development of the AI models as well as the sources of data, in order to gain the confidence of conservation workers (Jiang et al., 2017). Maintenance of quality in the data is a challenge, especially in countries where little data exists (Ripple et al., 2017).

3.9.2 Ethical Factors in AI-Driven Conservation

The ethical issues to consider include those of surveillance and privacy and the potential misuse of the technology. Using the drone and satellite surveillance technologies may infringe on the rights of the local communities (Spelda and Stritecky, 2020). Excessive use of AI may cause the relegation of Indigenous knowledge to the background in the process, which therefore creates a need to consider the importance of ethics in the use of AI.

3.9.3 Limitations and Barriers to Implementation

There might also exist technical challenges related to the cost of implementation, infrastructure, skills required for implementation and access to technological innovations, which can impede the uptake of AI systems in developing countries (Binley et al., 2024). Capacity building and sourcing funds are also crucial for the success of

conservation innovations and the elimination of technical challenges, thus fostering global conservation innovation equity (Kulkarni and Di Minin, 2023).

3.10 Future Directions and Emerging Technologies

Future directions in animal conservation depend on the integration of artificial intelligence into the fabric of emerging technologies and cross-disciplinary methods (Spelda and Stritecky, 2020). Accordingly, AI is likely to take an increasingly central role in predicting conservation needs and informing adaptive management (Pollock et al., 2020).

3.10.1 AI, Big Data and Forecasting Biodiversity

With AI meeting big data, powerful forecasts of how biodiversity may shift, which species may decline, and how ecosystems respond to environmental change are liberated (Christin et al., 2019). Predictive analytics become a tool for proactive planning, enabling managers to pre-empt threats well in advance rather than reacting after a problem has occurred (Pollock et al., 2020).

3.10.2 AI and Citizen Science in Harmony

Amateur science projects produce an ocean of data through apps, online platforms and local monitoring. AI validates, categorizes and analyses the crowd-sourced data at scale to up public engagement while maintaining scientific standards (Christin et al., 2019). The blending will raise conservation awareness among people.

3.10.3 Artificial Intelligence's Impact on Sustainable Conservation Policy

AI-powered insights definitely enable evidence-based policy decisions through the performance review of management efforts, optimization of resource allocations and the assessment of sustainability over a long period (Chen et al., 2020). Policymakers can use AI-driven models in bringing a balance between biodiversity protection and fulfilment of socio-economic objectives to ensure coexistence between humans and wildlife (Binley et al., 2024).

3.11 Conclusion

Artificial intelligence has emerged as an important helpmate to conservation practices for animal species, offering data-driven, efficient and flexible management of biodiversity. Conversely, when artificial intelligence combines with the biological sciences, critical issues affecting biodiversity, such as loss of habitats, poaching and climate change, do not seem daunting. The promising approach for creating a bright and secure future for wildlife and biodiversity relies on ethical governance, inter-disciplinary work and public engagement. Additionally, technology, biological sciences and society can come together in harmony to create a bright and secure future.

References

- [1] Binley, A. D., Peterson, A. T., and Di Minin, E. (2024). Making the most of existing data in conservation research. *Perspectives in Ecology and Conservation*, 22, 122–128. <https://doi.org/10.1016/j.pecon.2023.11.004>
- [2] Chen, T., Kornblith, S., Norouzi, M., and Hinton, G. (2020). A simple framework for contrastive learning of visual representations. *Advances in Neural Information Processing Systems*, 33, 1597–1607.
- [3] Christin, S., Hervet, É., and Lecomte, N. (2019). Applications for deep learning in ecology. *Methods in Ecology and Evolution*, 10(10), 1632–1644. <https://doi.org/10.1111/2041-210X.13256>
- [4] Ferraro, P. J., Sanchirico, J. N., and Smith, M. D. (2019). Causal inference in coupled human and natural systems. *Proceedings of the National Academy of Sciences of the United States of America*, 116(12), 5311–5318. <https://doi.org/10.1073/pnas.1805563115>
- [5] García-Roselló, E., González-Dacosta, J., and Lobo, M. (2023). The biased distribution of existing information on biodiversity hinders its use in conservation. *Biological Conservation*, 283, 110118. <https://doi.org/10.1016/j.biocon.2023.110118>
- [6] Gill, A. S. (2019). Artificial intelligence and international security: The long view. *Ethics and International Affairs*, 33(2), 169–179. <https://doi.org/10.1017/S0892679419000145>
- [7] Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., Wang, Y., Dong, Q., Shen, H., and Wang, Y. (2017). Artificial intelligence in healthcare: Past, present and future. *Stroke and Vascular Neurology*, 2(4), 230–243. <https://doi.org/10.1136/svn-2017-000101>
- [8] Krenn, M., Pollice, R., Guo, S. Y., Aldeghi, M., Cervera-Lierta, A., Friederich, P., and Aspuru-Guzik, A. (2022). On scientific understanding with artificial intelligence. *Nature Reviews Physics*, 4, 761–769. <https://doi.org/10.1038/s42254-022-00518-3>

- [9] Kulkarni, R., and Di Minin, E. (2023). Towards automatic detection of wildlife trade using machine vision models. *Biological Conservation*, 279, 109924. <https://doi.org/10.1016/j.biocon.2023.109924>
- [10] Pollock, L. J., Thuiller, W., and Jetz, W. (2020). Protecting biodiversity (in all its complexity): New models and methods. *Trends in Ecology and Evolution*, 35(12), 1119–1128. <https://doi.org/10.1016/j.tree.2020.08.015>
- [11] Ripple, W. J., Wolf, C., Newsome, T. M., Galetti, M., Alamgir, M., Crist, E., Mahmoud, M. I., and Laurance, W. F. (2017). World scientists' warning to humanity: A second notice. *BioScience*, 67(12), 1026–1028. <https://doi.org/10.1093/biosci/bix125>
- [12] Spelda, P., and Stritecky, V. (2020). The future of the human–artificial intelligence nexus and its environmental costs. *Futures*, 117, 102531. <https://doi.org/10.1016/j.futures.2020.102531>
- [13] Sutherland, W. J., Bennett, C., Brotherton, P. N. M., Butchart, S. H. M., Butterworth, H. M., Clarke, S. J., Esmail, N., Fleishman, E., Gaston, K. J., Herbert-Read, J. E., Hughes, A. C., James, J., Kaartokallio, H., Le Roux, X., Lickorish, F. A., Newport, S., Palardy, J. E., Pearce-Higgins, J. W., Peck, L. S., Pettorelli, N., Primack, R. B., Primack, W. E., Schloss, I. R., Spalding, M. D., ten Brink, D., Tew, E., Timoshyna, A., Tubbs, N., Watson, J. E. M., Wentworth, J., Wilson, J. D., and Thornton, A. (2024). A horizon scan of global biological conservation issues for 2024. *Trends in Ecology and Evolution*, 39(2), 89–100. <https://doi.org/10.1016/j.tree.2023.11.001>
- [14] Xu, L., Wang, Z., Liu, X., and Li, J. (2023). Enhanced persistent orientation of asymmetric-top molecules induced by cross-polarized terahertz pulses. *Physical Review Research*, 7(1), 013201. <https://doi.org/10.1103/PhysRevResearch.6.013201>

NOTES

This image shows a single sheet of white paper with horizontal ruling lines. The lines are evenly spaced and run across the width of the page. There are no margins, text, or other markings on the paper.

Chapter 4

ARTIFICIAL INTELLIGENCE FOR PHYSICAL SCIENCES

Mishu Gupta* & Charita Mehta

Assistant Professor, Department of Physics, Khalsa College for Women, Civil Lines, Ludhiana, Punjab, India-141001.

Email*: gupta1011mishu@gmail.com

Abstract

The use of Artificial Intelligence in the study of physics and natural phenomena has seen steady increase in the last 3 years. The development of AI into these analytical and experimental branches has seen a rise progressively, and has its unique contributions as well. The use of CNNs, GNNs, GANs, Transformers, among other methods has led to a significant analysis in the overall development of physics in the last few years. This article will give a short listing of the physics branches of classical mechanics, electromagnetism, statistical physics, thermodynamics and quantum physics. These branches have long standing implications in the development of engineering concepts as well as the applications that arise from them.

Keywords: Artificial Intelligence, Classical Physics, Statistical Physics, Thermodynamics, quantum mechanics

4.1 Introduction

The use of artificial intelligence in the development and understanding of new physics and technology has become an important part of the research landscape in the last 2-3 years. With an increase in computing capabilities, the process of ideation and simulation has received a boost in the last few years. The overall capabilities of the algorithms have also been worked upon and there are now existing several architectures in the literature (Jiao et al., 2024).

Since there is a ubiquitous application of these technologies in every area of commercial and research-based applications, we can create comparisons between the natures of algorithms for each of those applications. This article will take the reader through the various development paradigms that have been worked upon so far. The neural networks are highly effective at approximating complex nonlinear functions, while physics-based penalty terms help ensure that the learned solutions remain consistent with known theoretical values.

The process of revealing new relationships between variables has developed into a unique paradigm known as discovery of physics using artificial intelligence. Using algorithms of deep learning and machine learning as well as higher order architectures such as Transformers and Federated learning, it is now possible to represent physical systems using connected neural networks for the purpose of performing multi physics calculations. Even then, the phenomenon of “AI Blackbox” has been difficult to understand and the nature of hidden values inside the layers become difficult to interpret and understand without external knowledge. It must be noted that the development of AI to solve physics problems does not intend to replace the existing methodologies rather than only supplement them with a new tool. In this regard, the prime objective of AI introduction into physics is to use the findings of conventional physical sciences along with AI to investigate the processes in metaphysical learning as well as development of novel algorithms.

There are four key branches of physics, namely classical mechanics, electromagnetism, statistical and thermodynamics physics, and quantum mechanics. Each of these subjects has seen a lot of development in the last century using conventional theoretical and experimental techniques. The development of AI tools is meant to use existing models explaining behavior of complex systems and coming up with techniques to solve those models as well as validation from conventional numerical and analytical techniques. Therefore, it is imperative to note that both methods share the aims and goals but the implementation is different. Physics is meant to understand natural phenomena and develop theories that allow for predictive calculations. In such a scenario the role of AI would be to provide analysis and intelligence results based on the data.

4.2 Applications In Classical Mechanics

The laws of classical mechanics are based on the conservation of symmetries between systems. The overall conservation scenario is also based on certain assumptions in terms of how the systems have been defined before study. The laws of physics are generally considered invariant (or use invariant quantities), and objects follow translation symmetry in the form of conservation of momentum, or rotational symmetry in the form of conservation of angular momentum. Momentum conservation in general has been explained using symmetry as the definition from group theory. Noethers theorem gives a detailed understanding of the concept. Alongside space, there is another symmetry of time translation and relates to the conservation of energy. In this regard the translational invariance is very nicely predicted by convolutional neural networks. Any data that can be restructured in the form of an Euclidean matrix can be solved using such networks (Mahligawati et al., 2023; Yeadon and Hardy, 2024).

Developing these concepts further, we move on to the manifold neural networks. A manifold is a region that can be locally expressed by Euclidean properties. Each manifold is defined using its own metric. The algorithms that work in this area are specific to unsupervised learning. Some examples include multidimensional scaling, local linear embedding algorithms that are used for conservation of local linear features. This makes them useful for problems involving dimensionality reduction (Udrescu and Tegmark, 2020). Notably the UMAP (uniform manifold approximation algorithm has been made upon the Riemann manifold. Some highly influential works on such algorithms include (Babu and Pandit, 2025; Yeadon and Hardy, 2024), spectral embedding (Belkin and Niyogi, 2023; Harlim et al., 2023), diffusion maps (2012), gaussian manifold autoencoder by Cho et al. (2024) among others (Cho et al., 2025; Islam, 2025).

Another section of classical mechanics is fluid mechanics and dynamics. The last half century has seen the development of CFD as an excellent tool for simulation of fluid mechanics-based problems and has attracted a significant funding in research and development. CFD emerged from the integration of modern fluid mechanics with numerical methods. Maziar Raissi and collaborators

introduced a physics-informed deep learning framework known as the Hidden Fluid Mechanics (HFM) network. In this approach, the fundamental laws governing fluid motion including the continuity, transport, momentum, and energy equation are directly embedded into the neural network. Rather than learning purely from data, the network is trained to satisfy these physical laws through residual minimization. A major strength is its flexibility unlike traditional CFD approaches, this approach is less dependent on explicitly defined boundary and initial conditions and also it can effectively infer hidden flow dynamics from limited observations. The Neural Particle Method (NPM) (Bai et al., 2022), deep learning framework capable of automatically generating realistic fluid animations from Lagrangian fluid simulation data has demonstrated that neural networks can significantly speed up the simulation time compared to traditional approaches (Zago et al., 2026).

4.3 Applications In The Field of Electromagnetism

Differential equations play a fundamental role in physics and have increasingly inspired the design of modern neural network architectures. Researchers now treat neural networks as dynamical systems and use numerical differential equation methods to guide network design and training (Salucci et al., 2022). Physics-informed neural networks combine strong function approximation capabilities with penalty terms that enforce physical laws and theoretical constraints. These methods have been successfully applied to turbulence modeling, reinforcement learning, and switching dynamical systems (Salucci et al., 2022; Yeadon and Hardy, 2024; Zago et al., 2026). The introduction of latent ODEs further allows neural networks to model continuous-time and time-dependent processes effectively (Salucci et al., 2025).

Numerical methods such as the forward and backward Euler schemes also provide theoretical insight into deep learning architectures. For example, ResNet can be interpreted as a forward Euler discretization of a neural ODE, while architectures such as RevNet and PolyNet relate to more advanced dynamical system formulations. Overall, neural differential equation frameworks are seen to make a strong connection between machine learning, numerical analysis, and physical modeling. This makes it a powerful tool for understanding and simulating complex dynamic systems.

4.4 Applications In Statistical Physics

One important idea is the interpretation of neural networks in terms of entropy and information theory. Entropy was introduced first in thermodynamics. It is a measure of disorder or uncertainty in a system (Al-Raeei, 2025). In deep learning, the minimum entropy principle implies that decreasing the redundancy of information can be beneficial to the learning efficiency (Chinesta et al., 2021). This idea has inspired algorithms like Word2Vec, t-SNE and information-theoretic optimization methods (Chertkov, 2024). Another important direction is the study of chaotic neural networks, i.e. neural systems are studied as nonlinear dynamical systems that can switch between ordered and chaotic behaviors (Chertkov, 2024; Chinesta et al., 2021). Deep neural networks have been demonstrated to possess phase transitions similar to physical systems, affecting signal propagation, memory and learning stability. Statistical physics has also had a strong influence on neural network architectures, e.g. the Ising model (Babu and Pandit, 2025) and Hopfield networks (Alamino, 2024; Babu and Pandit, 2025).

Hopfield neural networks were developed for associative memory and combinatorial optimization, inspired by the Ising model originally developed to study magnetic phase transitions. The idea of energy-based learning was introduced by Hopfield networks, relating neural computation to the laws of physical energy minimization. Later, these models were applied to optimization, image encryption and chaotic systems. Thermodynamically based optimization methods have led to the development of simulated annealing algorithms. Simulated annealing is a metaheuristic inspired by annealing in materials, where a system probabilistically explores the search space to find global optima. Variants like Annealed Importance Sampling (AIS) and Hamiltonian AIS increased efficiency and decreased bias in probabilistic inference and rare-event estimation.

Another important contribution of statistical physics is the development of Boltzmann Machines (BM) and Restricted Boltzmann Machines (RBM). These are probabilistic neural networks that are closely related to the inverse of the Ising model. They are based on energy-based learning and simulated annealing. Their ability to learn hidden representations and to model complex data distributions has made RBMs important in AI applications. Later variants such

as convolutional and sparse RBMs have further enhanced their representational power and practical applications.

4.5 Conclusion

The article presents the development of algorithms that are relevant to the neural network and machine algorithms and has been prepared in this regard. The alignment of physics along with symmetry principles and the use of differential equations (ODEs and PDEs) using neural networks and related architectures has been a very useful tool in terms of getting accurate results and minimum computational cost for the solutions of systems. AI has now progressed into the use of combination of architectures that can be put up with Multiphysics to obtain solutions as well as predict future behavior.

References

- [1] Alamino, R. C. (2024). Explaining the Machine Learning Solution of the Ising Model (arXiv:2402.11701). arXiv. <https://doi.org/10.48550/arXiv.2402.11701>
- [2] Al-Raei, M. (2025). Integrating artificial intelligence into thermodynamics: A new paradigm for sustainable future. *AIP Advances*, 15(6), 060701. <https://doi.org/10.1063/5.0271867>
- [3] Babu, V. K., and Pandit, R. (2025). Artificial intelligence and machine learning for phases and transitions in the Ising model: An overview. *The European Physical Journal B*, 98(12), 258. <https://doi.org/10.1140/epjb/s10051-025-01105-y>
- [4] Bai, J., Zhou, Y., Ma, Y., Jeong, H., Zhan, H., Rathnayaka, C., Sauret, E., and Gu, Y. (2022). A general Neural Particle Method for hydrodynamics modeling. *Computer Methods in Applied Mechanics and Engineering*, 393, 114740. <https://doi.org/10.1016/j.cma.2022.114740>
- [5] Chertkov, M. (2024). Mixing artificial and natural intelligence: From statistical mechanics to AI and back to turbulence. *Journal of Physics A: Mathematical and Theoretical*, 57(33), 333001. <https://doi.org/10.1088/1751-8121/ad67bb>
- [6] Chinesta, F., Cueto, E., Grmela, M., Moya, B., Pavelka, M., and Šípka, M. (2021). Learning Physics from Data: A Thermodynamic Interpretation. In F. Barbaresco and F. Nielsen (Eds.), *Geometric Structures of Statistical Physics, Information Geometry, and Learning* (pp. 276–297). Springer International Publishing. https://doi.org/10.1007/978-3-030-77957-3_14
- [7] Cho, M., Seong, Y., and Won, J. -H. (2025). Pareto Variational Autoencoder. *The Fourteenth International Conference on Learning Representations*. <https://openreview.net/forum?id=s5a8zBPFfe>

- [8] Harlim, J., Jiang, S. W., and Peoples, J. W. (2023). Radial Basis Approximation of Tensor Fields on Manifolds: From Operator Estimation to Manifold Learning. *Journal of Machine Learning Research*, 24(345), 1–85.
- [9] Islam, M. A. (2025). AI-Driven Simulations and Predictions: Transforming Theoretical and Experimental Physics. *British Journal of Physics Studies*, 3(1), 01–11. <https://doi.org/10.32996/bjps.2025.3.1.1>
- [10] Jiao, L., Song, X., You, C., Liu, X., Li, L., Chen, P., Tang, X., Feng, Z., Liu, F., Guo, Y., Yang, S., Li, Y., Zhang, X., Ma, W., Wang, S., Bai, J., and Hou, B. (2024). AI meets physics: A comprehensive survey. *Artificial Intelligence Review*, 57(9), 256. <https://doi.org/10.1007/s10462-024-10874-4>
- [11] Mahligawati, F., Allanas, E., Butarbutar, M. H., and Nordin, N. A. N. (2023). Artificial intelligence in Physics Education: A comprehensive literature review. *Journal of Physics: Conference Series*, 2596(1), 012080. <https://doi.org/10.1088/1742-6596/2596/1/012080>
- [12] Salucci, M., Arrebola, M., Shan, T., and Li, M. (2022). Artificial Intelligence: New Frontiers in Real-Time Inverse Scattering and Electromagnetic Imaging. *IEEE Transactions on Antennas and Propagation*, 70(8), 6349–6364. <https://doi.org/10.1109/TAP.2022.3177556>
- [13] Salucci, M., Li, M., and Massa, A. (2025). AI-Driven Approaches for Solving Electromagnetic Inverse Problems. In *Artificial Intelligence for Future Networks* (pp. 257–281). John Wiley and Sons, Ltd. <https://doi.org/10.1002/9781394227952.ch8>
- [14] Udrescu, S.-M., and Tegmark, M. (2020). AI Feynman: A physics-inspired method for symbolic regression. *Science Advances*, 6(16), eaay2631. <https://doi.org/10.1126/sciadv.aay2631>
- [15] Yeadon, W., and Hardy, T. (2024). The impact of AI in physics education: A comprehensive review from GCSE to university levels. *Physics Education*, 59(2), 025010. <https://doi.org/10.1088/1361-6552/ad1fa2>
- [16] Zago, V., Amato, E., and Del Negro, C. (2026). A lagrangian AI-based CFD emulator with reconstruction of Hydrodynamic forces components. *Computers and Fluids*, 313, 107059. <https://doi.org/10.1016/j.compfluid.2026.107059>

Chapter 5

AI TOOLS IN CHEMISTRY

Promila Nagpal

Assistant Professor, Vishnu Waman Thakur Charitable Trust's, Bhaskar Waman Thakur College of Science, Yashvant Keshav Patil College of Commerce, Vidhya Dayanand Patil College of Arts, Virar West, Taluka Vasai, Thane, Maharashtra, India- 401303.

Email: promila.nagpal@vivacollege.org

Abstract

Artificial Intelligence (AI) tools are playing a vital role in the field of chemistry by enhancing research efficiency, accuracy and innovation across various research disciplines. By integrating machine learning, deep learning and data-driven algorithms, AI enables chemists to analyze complex chemical data and predict outcomes that were earlier time-consuming or computationally expensive. In drug discovery and pharmaceutical chemistry, AI boost the identification of new drugs by predicting molecular properties, biological activities and drug target interactions, significantly reducing development time and cost. In materials science, AI supports the rational design of new materials, catalysts and polymers by correlating chemical structure with physical and chemical properties. AI tools also help in chemical reaction prediction and synthesis planning, where method can forecast reaction pathways, optimize conditions and propose efficient synthetic routes. In analytical and organic chemistry, AI improves the interpretation of spectroscopic and chromatographic data, enabling rapid and accurate identification of compounds and impurities. Furthermore, AI-based models complement traditional computational chemistry by approximating quantum mechanical calculations, allowing the study of large and complex molecular systems with reduced computational resources. AI also contributes to green and sustainable chemistry by aiding in the

development of environmentally friendly processes, minimizing waste and optimizing energy efficiency. Overall, AI tools are reshaping modern chemistry by accelerating discovery, improving decision-making and fostering sustainable scientific advancement, making them indispensable in both academic research and industrial applications.

Keywords: Green Chemistry, Artificial intelligence, AI Tools, Chemical Sciences

5.1 Introduction

Chemistry is a science that deals with the study of matter, composition, its properties, reactions and transformations. Traditional chemical research relies heavily on empirical trial and error, experimental procedures, distillation, theoretical calculations and human intuition. While these methods have led to groundbreaking discoveries, (Back et al., 2024) they are often time-consuming, expensive and limited by human cognitive capacity. It traditionally bridges academic theory with industrial applications in various disciplines.

Artificial Intelligence (AI) is revolutionizing chemistry by offering a powerful solution to these challenges. AI refers to computational systems capable of learning from data, recognizing patterns and making predictions or decisions with minimal human intervention. AI tools can analyze massive datasets, predict molecular behavior, optimize reactions and even propose new compounds with desired properties in chemical sciences (Boiko et al., 2023).

AI has become a vital tool in scientific research, educational industry in recent years. Its applications range from drug discovery and materials science to environmental chemistry and industrial process optimization (Cagno et al., 2021). This chapter provides a comprehensive overview of AI tools in chemistry and highlights their impact on the future of the discipline.

The incorporation of Artificial Intelligence into chemistry has greatly enhanced the efficiency of drug discovery and development processes. Advanced machine learning techniques enable the rapid evaluation of extensive chemical libraries, prediction of biological activities, and identification of promising drug candidates with improved precision compared to traditional approaches. This

significantly minimizes the time and financial resources required for experimental validation and clinical studies. Moreover, AI models contribute to a deeper understanding of complex biological systems, facilitating the development of highly specific and effective therapeutic compounds (Mater et al., 2019).

In materials science, Artificial Intelligence has become an essential tool for the innovation and design of materials with customized properties. By processing and interpreting large volumes of data related to material structures and behaviors, AI systems can forecast the performance of novel materials under different conditions. This has accelerated progress in fields such as renewable energy, nanoscience, and sustainable material development. As a result, AI not only streamlines research activities but also supports efforts to tackle pressing global issues related to resource management and environmental sustainability (Aspuru-Guzik et al., 2018).

Furthermore, the use of Artificial Intelligence in environmental chemistry and industrial applications has led to advancements in monitoring, analysis, and process optimization. AI-driven technologies are capable of identifying environmental contaminants, predicting ecological trends, and recommending effective pollution control measures. In industrial operations, AI assists in refining reaction parameters, enhancing product yield, and maintaining safety standards by reducing the likelihood of human error. Therefore, the implementation of AI is promoting greener, safer, and more efficient chemical practices, representing a major progression in the field of chemistry (Capella et al., 2020).

5.2 Overview of Artificial Intelligence

Artificial Intelligence encloses a broad range of computational techniques designed to simulate human intelligence. The main branches of AI related to chemistry include:

5.2.1 Machine Learning (ML)

Machine learning enables computers to learn patterns from data without being explicitly programmed. ML models are trained using experimental or computational datasets to predict chemical properties and outcomes in chemistry discipline. The Common ML methods are Linear and nonlinear regression, Decision trees,

Support vector machines and Random forests (Capella et al., 2020)
The machine learning workflow follows various steps:

- **Data Gathering and Preparation:** During the experimental or databases phase, data is collected, cleaned and pre-processed.
- **Representation:** Translating chemical structures into computer readable-formats.
- **Model Training:** The prepared data is fed into a chosen learning algorithm (e.g., linear regression, neural networks).
- **Testing and Validation:** Evaluating accuracy on unseen data.

5.2.2 Deep Learning (DL)

Deep learning is a subset of machine learning that uses artificial neural networks with multiple layers. These networks are effective for analyzing complex chemical data such as molecular structures, spectral and images (Yann LeCun et al., 2019). The common key deep learning methodologies are:

- Graph Neural Networks (GNNs) are designed to work with graph-structured data where information is organized as nodes and edges.
- Generative Models (VAEs and GANs) learns how data is distributed and then generates new samples from that distribution.
- Recurrent Neural Networks (RNNs) and Transformers are designed for sequential data, where the order matters.
- Convolutional Neural Networks (CNNs) are used for image and visual data.
- Reinforcement Learning (RL) is used to guide generative models creating molecules with certain optimized properties.

5.2.3 Natural Language Processing (NLP)

According to IBM (2024), NLP allows AI systems to understand, interpret and process human language. In chemistry, NLP tools are used to analyse scientific literature, patents and lab notes. The core components of NLP are:

- **Lexical Analysis for words and tokens:** According to Bird, S. (2009), Lexical analysis involves breaking down text into smaller units such as words, phrases, or tokens. It helps in identifying the basic elements of language and removing

unnecessary characters. This step is essential for further processing in NLP.

- **Syntactic Analysis for grammar and sentence structure:** Syntactic analysis focuses on understanding the grammatical structure of a sentence. It determines how words are arranged and related to each other. This helps in checking sentence correctness and parsing its structure (Jurafsky and Martin, 2023).
- **Semantic Analysis for meaning of words/sentences:** Semantic analysis is concerned with interpreting the meaning of words and sentences. It identifies relationships between words and resolves ambiguities. This step ensures that the actual intent of the text is understood (Jurafsky and Martin, 2023).
- **Pragmatic Analysis for context-based meaning:** Pragmatic analysis deals with understanding language in its context. It considers real-world knowledge, speaker intent, and situational factors. This helps in deriving the intended meaning beyond literal interpretation (Jurafsky and Martin, 2023).

5.2.4 Computer Vision

Computer vision enables AI systems to interpret visual data such as microscopy images, crystal structures and reaction monitoring videos similar to human vision. The basic computer vision pipeline is

- **Image acquisition- camera/sensor input:** This is the first step where visual data is captured using cameras, microscopes, or sensors. The quality of input images directly affects the accuracy of the system. Proper acquisition ensures reliable data for further analysis (Jain, 1989).
- **Preprocessing- resize, noise removal and normalization:** In this stage, raw images are cleaned and standardized to improve quality. It includes resizing, removing noise, and adjusting brightness or contrast. This step enhances image clarity and prepares it for feature extraction (Sonka et al., 2014).
- **Feature extraction- edges, shapes, textures:** Feature extraction identifies important patterns such as edges, shapes, and textures within an image. These features help in distinguishing different objects or structures. It reduces data complexity while preserving essential information (Haralick et al., 1973).

- **Modeling- ML/Deep Learning (CNNs):** Here, machine learning or deep learning models, especially Convolutional Neural Networks (CNNs), are used to learn patterns from the extracted features. The model is trained to recognize and interpret visual data. This step forms the core intelligence of the system (LeCun et al., 1998).
- **Decision making – classification, detection, recognition:** In the final step, the system makes predictions based on the trained model. It can classify images, detect objects, or recognize patterns. This output is used for practical applications like analysis and automation (Jain et al., 2000).

5.3 Why Chemistry Needs AI

There are several challenges in chemistry that make it ideal for AI integration:

- **Large and complex datasets:** Modern chemical research generates enormous amounts of data from experiments, simulations, and analytical instruments. Managing and interpreting this data manually is difficult and time-consuming. AI helps in efficiently organizing, analyzing, and extracting meaningful patterns from such complex datasets (Boiko et al., 2023).
- **Predicting chemical reactions:** Accurately predicting the outcome of chemical reactions is challenging due to the involvement of multiple variables and conditions. Traditional methods rely heavily on experience and trial-and-error. AI models can analyze past reaction data to predict products, reaction pathways, and yields with higher accuracy (Schwaller et al., 2021).
- **High cost of experiments:** Chemical experiments often require expensive equipment, materials, and significant labor. Repeated trials increase overall costs and resource consumption. AI reduces these expenses by optimizing experimental design and minimizing unnecessary trials (Aspuru-Guzik et al., 2018).
- **Slow discovery cycles:** The process of discovering new compounds or materials is typically slow and involves multiple stages of testing and validation. This delays innovation and practical applications. AI accelerates discovery by rapidly

screening and identifying promising candidates (Boiko et al., 2023).

- **Complex molecular interactions:** Understanding interactions at the molecular level is difficult due to the complexity of chemical structures and bonding behaviors. These interactions often involve subtle changes that are hard to predict. AI can model and simulate these interactions more effectively, improving accuracy in analysis (Mater et al., 2019).
- **Human bias and error:** Traditional research methods depend on human judgment, which can introduce bias and errors in experimentation and interpretation. Mistakes in data handling or assumptions may affect outcomes. AI provides more objective, data-driven insights, reducing the influence of human limitations (Boiko et al., 2023).

AI tools can process chemical data faster, smarter, safer, cheaper and more accurately than traditional methods, allowing chemists to focus on interpretation and innovation rather than repetitive tasks.

5.4 Major AI Tools Used In Chemistry

- i. **AI-driven Drug Discovery:** AI tool can be used to accelerate the target identification of potential drug candidates through the prediction of biological activity and optimization of lead compounds with tools like AlphaFold (Galushko et al., 2023).
- ii. **Big Data and Integrated Data:** Consolidation and harmonization of diverse chemical data sources, industrial processes, facilitating cross-disciplinary research and comprehensive data analysis. AI driven tools such as DeepChem, ChemCopilot and IBM RXN, utilize machine learning and neural networks to accelerate drug discovery, optimize molecular design and enable automated synthesis planning (Lee et al., 2023).
- iii. **Automated Laboratory Platforms:** Development of automated laboratory systems for conducting experiments with least human intervention, improving precision, reproducibility and accelerating chemical discovery (Keith et al., 2021). AI tools are ChemCopilot, Albert Invent, IKtos, DeepChem, Chemspeed's robotic platforms and IBM's RoboRXN.
- iv. **Integration of Laboratory Instruments and IoT:** Laboratory instrument connectivity to the Internet of Things (IoT) for

Table 5.1: AI Drug Discovery Comparison (Vamathevan et al., 2019)

Process Stage	Traditional Approach	AI-Accelerated Approach
Time Required	10–15 years	3–6 years
Cost	More than \$2 Billion	70% Cost Reduction
TargetIdentification	Manual, time-consuming research	Faster using AI algorithms
Molecule Design	Trial-and-error based	AI-driven predictive design
Property Prediction	Experimental testing	Computational prediction (ML models)
Clinical Trials	Long and expensive	Optimized and faster with AI insights

real-time data collection, monitoring and improved operational analysis. By connecting instruments like freezers, sensors and analyzers to LIMS or cloud platforms, predictive maintenance, reduced human error and data- driven research (Zheng and Yi, 2023).

- v. **AI in Spectroscopy and Analytical Method Development:** AI applications revolutionize complex spectroscopic data interpretation, enabling faster, more accurate and developing novel analytical methods. Tools like convolutional neural networks (CNN), deep learning (DL) and chemometric models (partial least squares) are used for spectral deconvolution, pattern recognition and improved chromatographic separation. These tools accelerate sensitivity in Raman, NMR and IR spectroscopy (Marini, 2021).
- vi. **Blockchain in Chemical Supply Chain:** Blockchain technology is transforming the chemical supply for secure, transparent chemical and material supply chain tracking. It addresses critical challenges in the chemical industry. A notable AI tool NVIDIA ALCHEMI accelerates stimulation data generation 1600 times faster, speeding up chemical research (Sara et al., 2019).
- vii. **Digital Twins:** This method is transforming the chemistry and chemical manufacturing sector by Creation of virtual replicas of chemical processes or systems for simulation, monitoring, and optimization purposes (Fuller et al., 2020).
- viii. **Virtual Laboratories and Augmented Reality:** These tools enable users to visualize digital platforms and simulation software enhancing teaching and providing virtual lab experiences. Key platforms include Labster and PhET stimulations for virtual laboratories (David et al., 2020).
- ix. **Natural Language Processing (NLP) in Chemical Space:** NLP tools such as ChemNLP, ChemFast Text-Tuned, and LLMs like GPT-4/Galactica automate the mining of chemical information from scientific literature, patents and databases for knowledge extraction (Gomes et al., 2023).
- x. **Predictive Toxicology:** This technology uses computational models for predicting chemical toxicity to enhance environment protection and chemical manufacturing safety (White et al., 2021).

- xi. AI in Environmental Chemistry and Sustainability: Digital tools aiding environmental process analysis, eco-friendly solvents, designing catalysts to control pollution and green chemistry development (Mahjour et al., 2023)
- xii. Machine Learning in Molecular Design: Techniques like Graph neural networks (GNNs) and generative models explore application of ML algorithms to predict molecular properties, enabling efficient design of new compounds and materials (Matsubara et al., 2022).
- xiii. Smart Control: Implementation of intelligent control systems in chemical processes and various equipments, enabling adaptive and optimized operations. Smart control in Artificial Intelligence refers to the use of advanced algorithms and data-driven models to automatically monitor and regulate chemical processes and equipment. Unlike traditional control methods, smart control can adapt to changing process conditions, predict potential issues, and take corrective actions without human intervention. This leads to improved efficiency, enhanced safety, reduced energy consumption, and better product quality in chemical and industrial operations (Segler et al., 2018).
- xiv. Deep Learning in Structure-Activity Relationships (SAR): The application of deep learning models to decipher and predict the complex relationships between chemical structures and their biological activities enhances the efficiency of drug discovery processes (Toninato et al., 2023).
- xv. AI-driven High-throughput Experimentation (HTE): Robotics, automated liquid handlers and AI integration for conducting and analyzing multiple parallel experiments, accelerating the research process by testing hundreds or thousands of conditions simultaneously (Boiko et al., 2023).
- xvi. Digital Materials Design and Materials Informatics: This tool accelerates material design by using artificial intelligence. Data-driven approaches are used for discovering and designing novel materials with desired properties and applications (Kristin and Persson, 2016).
- xvii. Data-Driven Chemical Reaction Optimization: Machine intelligence models are used for predicting reaction outcomes, optimizing conditions, and discovering new reactivity (Coley et al., 2019).

- xviii. Automated Synthesis Planning: Assistance is taken from AI tools in planning and optimizing synthetic routes, reducing experimental trial time and resources (Coley et al., 2018).
- xix. Chemo informatics and Chemical Data Analysis: These tools provide advanced techniques for managing and interpreting large chemical datasets, enhancing understanding of complex relationships in chemical structures and processes (Toyao et al., 2020)
- xx. AI in Quantum Chemistry and Simulations: AI-enhanced accuracy and efficiency in quantum chemical calculations and molecular simulations is achieved using this tool (Yang et al., 2020).

5.5 Conclusion

With the arrival of the modern age, digital chemistry has emerged as a transformative shift in the field, utilizing computational capabilities, machine learning techniques and extensive datasets to enhance and accelerate discovery. This digital transformation provides exceptional predictive strength, improved efficiency and the capacity to address highly complex challenges that traditional approaches alone cannot resolve. It suggests a transition toward more focused, hypothesis-oriented investigations, decreasing dependence on accidental discoveries and making research more structured and resource-efficient.

It is important to recognize that several of the top 20 identified digital research directions intersect and, at times, pursue similar objectives through slightly varied methodologies (Zheng et al., 2023). Given the novelty and rapid development of this domain, clearly distinguishing boundaries between individual digital pathways or defining precise segments within chemical research can be challenging. Although overlaps in techniques and targeted outcomes may occur, the principal trajectories identified through analysis of current research data are presented as observed. No effort was made to manually consolidate or modify overlapping trends. A more refined classification and systematization may become possible in the future as additional developments emerge and their impacts become clearer.

The advancement of chemical science will depend on the integration of these varied approaches. Traditional chemistry continues to offer essential value, especially in educational settings and in contexts requiring direct interaction with materials. At the same time, digital chemistry is poised to expand further, stimulate innovation and empower scientists to explore the immense chemical landscape with greater precision and efficiency than ever before.

Organizing developments into thematic categories clarifies the broad influence of artificial intelligence on chemistry, revealing both significant progress and the global issues being addressed. Together, these themes reflect a movement away from purely experimental, labor-intensive practices toward more predictive, streamlined and accelerated research enabled by digital technologies. As chemistry enters its digital phase, these thematic areas will strongly influence research agendas, industrial strategies and educational frameworks, promoting innovation, sustainability and international cooperation. The incorporation of AI and digital tools not only reshapes research methodologies but also extends chemistry's reach, relevance and accessibility, signaling a new stage in scientific and technological advancement.

Although this study aimed to provide a thorough analysis, certain limitations must be acknowledged. Despite its comprehensive scope, the review may not fully capture or accurately anticipate every emerging trend within the fast-evolving field of digital chemistry and AI-driven applications. The continuous pace of technological innovation and its cross-disciplinary effects make it difficult to predict all future directions and consequences with certainty (Zhou et al., 2022). These limitations underscore the complexity of forecasting developments in such a dynamic area and recognize that some emerging patterns may not be fully identified or interpreted within the boundaries of this work.

Looking ahead, the key challenge and opportunity for the chemical research community lies in harmonizing essential elements, combining the indispensable intuition and experience derived from classical methods with the analytical strength of digital technologies. Such integration will deepen understanding and expand capabilities while preserving the creativity and exploratory spirit that define chemistry. By uniting these approaches, future chemists will be better equipped

to operate within an increasingly complex and interdisciplinary environment, fostering innovations that confront some of the most critical challenges facing society today.

References

- [1] Aspuru-Guzik, A., Hachmann, T. D., and Isayev, O. (2018). The role of machine learning in the understanding and design of materials. *Nature*, 559, 547–555. <https://doi.org/10.1038/s41586-018-0337-2>
- [2] Bird, S., Klein, E., and Loper, E. (2009). Natural language processing with Python. O'Reilly Media.
- [3] Boiko, D. A., MacKnight, R., Kline, B., and Gomes, G. (2023). Autonomous chemical research with large language models. *Nature*, 624(7992), 570–578. <https://doi.org/10.1038/s41586-023-06792-0>
- [4] Bogusevski, D. B., Muntean, C., and Muntean, G. M. (2020). Teaching and learning chemistry using augmented reality. *Smart Learning Environments*, 7(1), 1–17. <https://doi.org/10.1186/s40561-020-00117-0>
- [5] Cagno, E., Neri, A., Negri, M., Bassani, C. A., and Lampertico, T. (2021). The role of digital technologies in operationalizing the circular economy transition: A systematic literature review *Applied Sciences*, 11, 3328. <https://doi.org/10.3390/app11083328>
- [6] Capella, J. V., Bonastre, A., Campelo, J. C., Ors, R., and Peris, M. (2020). IoT and environmental analytical chemistry: Towards a profitable symbiosis. *Trends in Environmental Analytical Chemistry*, 27, e00095. <https://doi.org/10.1016/j.teac.2020.e00095>
- [7] Coley, C. W., et al. (2019). A graph-convolutional neural network model for the prediction of chemical reactivity. *Chemical Science*, 10(2), 370–377. <https://doi.org/10.1039/C8SC04228D>
- [8] Coley, C. W., Green, W. H., and Jensen, K. F. (2018). Machine learning in computer-aided synthesis planning. *Accounts of Chemical Research*, 51(5), 1281–1289. <https://doi.org/10.1021/acs.accounts.8b00087>
- [9] Fuller, A., Fan, Z., Day, C., and Barlow, C. (2020). Digital twin: Enabling technologies, challenges and open research. *IEEE Access*, 8, 108952–108971. <https://doi.org/10.1109/ACCESS.2020.2998358>
- [10] Galushko, A. S., Boiko, D. A., Pentsak, E. O., Eremin, D. B., and Ananikov, V. P. (2023). Time-resolved formation and operation maps of Pd catalysts suggest a key role of single atom centers in cross-coupling. *Journal of the American Chemical Society*, 145, 9092–9103. <https://doi.org/10.1021/jacs.3c01892>
- [11] Ha, T., Lee, D., Kwon, Y., Park, M. S., Lee, S., Jang, J., Choi, B., Jeon, H., Kim, J., Choi, H., Seo, H. T., Choi, W., Hong, W., Park, Y. J., Jang, J., Cho, J., Kim, B., Kwon, H., Kim, G., Oh, W. S., Kim, J. W., Choi, J., Min, M., Jeon, A., Jung, Y., Kim, E., Lee, H., and Choi, Y. S. (2023). AI-driven robotic chemist

- for autonomous synthesis of organic molecules. *Science Advances*, 9. <https://doi.org/10.1126/sciadv.adh1852>
- [12] Haralick, R. M., Shanmugam, K., and Dinstein, I. (1973). Textural features for image classification. *IEEE Transactions on Systems, Man, and Cybernetics*, SMC-3(6), 610–621. <https://doi.org/10.1109/TSMC.1973.4309314>
- [13] Jain, A. K. (1989). Fundamentals of digital image processing. Prentice Hall.
- [14] Jain, A. K., Duin, R. P. W., and Mao, J. (2000). Statistical pattern recognition: A review. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 22(1), 4–37. <https://doi.org/10.1109/34.824819>
- [15] Keith, J. A., Vassilev-Galindo, V., Cheng, B., Chmiela, S., Gastegger, M., Müller, K. R., and Tkatchenko, A. (2021). Combining machine learning and computational chemistry for predictive insights into chemical systems. *Chemical Reviews*, 121, 9816–9872. <https://doi.org/10.1021/acs.chemrev.1c00107>
- [16] LeCun, Y., Bengio, Y., and Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436–444. <https://doi.org/10.1038/nature14539>
- [17] LeCun, Y., Bottou, L., Bengio, Y., and Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11), 2278–2324. <https://doi.org/10.1109/5.726791>
- [18] Mahjour, B., Hoffstadt, J., and Cernak, T. (2023). Designing chemical reaction arrays using phactor and ChatGPT. *Organic Process Research and Development*, 27, 1510–1516. <https://doi.org/10.1021/acs.oprd.3c00159>
- [19] Marini, F. (2021). Artificial intelligence and chemometrics in analytical chemistry. *Analytica Chimica Acta*, 1185, 338–350. <https://doi.org/10.1016/j.aca.2021.338350>
- [20] Mater, A. C., and Coote, M. L. (2019). Deep learning in chemistry. *Journal of Chemical Information and Modeling*, 59(6), 2545–2559. <https://doi.org/10.1021/acs.jcim.9b00266>
- [21] Matsubara, S. (2020). Digitization of organic synthesis—How synthetic organic chemists use AI technology. *Chemical Letters*, 50, 475–481. <https://doi.org/10.1246/cl.200851>
- [22] Persson, K. A. (2016). Materials genomics: From big data to materials discovery. *Nature Reviews Materials*, 1(1), 1–2. <https://doi.org/10.1038/natrevmats.2015.2>
- [23] Saberi, S., Kouhizadeh, M., Sarkis, J., and Shen, L. (2019). Blockchain technology and its relationships to sustainable supply chain management. *International Journal of Production Research*, 57(7), 2117–2135. <https://doi.org/10.1080/00207543.2018.1533261>

- [24] Schwaller, P., Laino, T., et al. (2021). Prediction of chemical reaction yields using deep learning. *Machine Learning: Science and Technology*, 2(1), 015016. <https://doi.org/10.1088/2632-2153/abc81d>
- [25] Segler, M. H. S., Preuss, M., and Waller, M. P. (2018). Planning chemical syntheses with deep neural networks and symbolic AI. *Nature*, 555, 604–610. <https://doi.org/10.1038/nature25978>
- [26] Sonka, M., Hlavac, V., and Boyle, R. (2014). Image processing, analysis, and machine vision(4th ed.). Cengage Learning.
- [27] Toniato, A., Schilter, O., and Laino, T. (2023). The role of AI in driving the sustainability of the chemical industry. *CHIMIA*, 77, 144–149. <https://doi.org/10.2533/chimia.2023.144>
- [28] Toyao, T., Maeno, Z., Takakusagi, S., Kamachi, T., Takigawa, I., and Shimizu, K. (2020). Machine learning for catalysis informatics: Recent applications and prospects. *ACS Catalysis*, 10, 2260–2297. <https://doi.org/10.1021/acscatal.9b04186>
- [29] Vamathevan, J., Clark, D., Czodrowski, P., Dunham, I., Ferran, E., Lee, G., Li, B., Madabhushi, A., Shah, P., Spitzer, M., and Zhao, S. (2019). Applications of machine learning in drug discovery and development. *Nature Reviews Drug Discovery*, 18(6), 463–477. <https://doi.org/10.1038/s41573-019-0024-5>
- [30] White, A., and Muddiman, D. C. (2021). Machine learning and AI in toxicology. *Chemical Research in Toxicology*, 34(2), 231–244. <https://doi.org/10.1021/acs.chemrestox.0c00317>
- [31] Yang, W., Fidelis, T. T., and Sun, W. H. (2020). Machine learning in catalysis: From proposal to practice. *ACS Omega*, 5, 83–88. <https://doi.org/10.1021/acsomega.9b03673>
- [32] Zheng, G., and Yi, L. (2023). An early warning method of abnormal state of laboratory equipment based on Internet of Things and running big data. *Web Intelligence*, 21(3). <https://doi.org/10.3233/WEB-220052>
- [33] Zheng, Z., Zhang, O., Borgs, C., Chayes, J. T., and Yaghi, O. M. (2023). ChatGPT chemistry assistant for text mining and the prediction of MOF synthesis. *Journal of the American Chemical Society*, 145, 18048–18062. <https://doi.org/10.1021/jacs.3c07076>
- [34] Zhou, X., and Kraft, M. (2022). Blockchain technology in the chemical industry. *Annual Review of Chemical and Biomolecular Engineering*, 13, 347–371. <https://doi.org/10.1146/annurev-chembioeng-092220-120402>

NOTES

This image shows a single sheet of white paper with horizontal ruling lines. The lines are evenly spaced and run across the width of the page. There are no margins, text, or other markings on the paper.

Chapter 6

MATHEMATICS BEHIND ARTIFICIAL INTELLIGENCE

Tejinder Kaur

Assistant Professor, P. G. Department of Mathematics, Khalsa College for Women, Civil Lines, Ludhiana, Punjab, India- 141001.

Email: tejinderkaur.kcw@gmail.com

Abstract

Artificial Intelligence (AI) has become an integral part of science and technology. Its rapid expansion and influence have led to a paradigm shift in the way research is advancing. The transformative effect can be widely seen in the diverse domains like healthcare, education, environmental science, engineering, social studies etc. Its impact shows data is analyzed, patterns are identified, and decisions are made with precision. Modern AI systems are capable of performing tasks that require complex reasoning, adaptive learning and predictive insights. With the rapid increase in AI applications across various disciplines, it is essential to understand their underlying principles to develop accurate systems. This chapter explores the mathematical principles that form the foundation of AI and the structure through which AI is conceived, examined and implemented. It discusses how mathematics is applied to build intelligent systems. The chapter highlights the roles of linear algebra, optimization techniques, discrete mathematics, calculus, probability, and statistics in helping the machines learn from data thereby improving their performance. These domains collectively guide the AI systems to learn, predict, generalize and evolve with time. The aim of the chapter is to emphasize the importance of studying and understanding mathematics in developing rigorous frameworks to develop more efficient and reliable models which is essential for effectively applying AI

technologies.

Keywords: Artificial Intelligence, Machine Learning, Mathematics, Optimization Techniques, Statistics

6.1 Introduction

Artificial Intelligence (AI) has become a part of our everyday life from unlocking our smart phones through face and fingerprint recognition, to voice assistants like Alexa and Siri. From using Google maps to find the shortest route, to applications like Uber and Ola for matching drivers and passengers, AI is integral to our daily routine. Though artificial intelligence is usually referred in terms of intelligent machines and smart applications, it is inherently a mathematical science (Golec et al., 2025). Every AI system like weather forecasting, healthcare diagnostics (Abbasi, 2025), industrial automation etc. relies on mathematics to process the data, analyses it, extract patterns from it and to arrive at decisions. Data collected from physical, biological, social, or economic systems is converted into numerical form and organized using matrices, vectors, graphs, or probability distributions. Mathematical modelling converts this data into structured and usable form for intelligent systems to optimize parameters and make precise predictions.

This chapter explores the role of linear algebra to perform matrix operations required for computations in AI systems like neural networks. It discusses how calculus and optimization are necessary for learning algorithms to adjust parameters and minimize errors. The chapter discusses the contribution of probability and statistics in addressing uncertainty and variability in real world data and the role of discrete mathematics in logical reasoning and algorithm design. These mathematical frameworks are essential for planning, language processing and for meaningful and responsible application of AI.

The remaining chapter is structured as follows. Section 2 discusses how data is represented and processed mathematically in AI systems by exploring the roles of linear algebra, probability and statistics, calculus and optimization, and discrete mathematics in advancing AI systems. Section 3 highlights the pedagogical and scientific significance of mathematical literacy in the AI era. The chapter

concludes by reflecting on the continuing role of mathematics as the foundation of AI development.

6.2 Mathematical Representation of Data In Artificial Intelligence

Every artificial intelligence system has data at its core, which must be converted into a form that the machine can understand and interpret. Images, texts, audio, measurements are transformed into numbers which form the base of the mathematical structures (Sinha et al., 2024). This is known as data representation which acts as the foundational layer for the learning algorithms to operate. The mathematical representation of observations into structured numerical forms allows the AI systems to operate, learn effectively and make decisions. Also, mathematics acts a bridge in feature selection and extraction from large amount of data, resulting in AI systems to recognize patterns and measure similarity and difference. Figure 6.1 illustrates process followed in building an AI system. Mathematical operations are involved in each stage of this process, beginning from data collection to model evaluation.

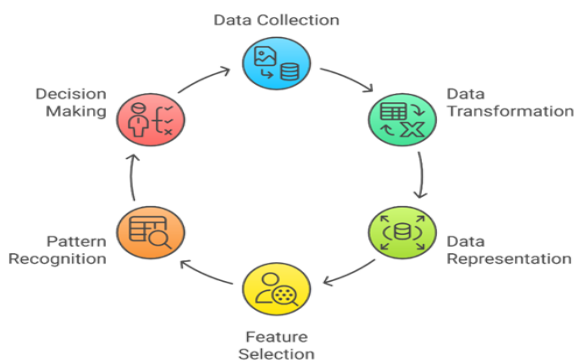


Figure 6.1: AI Data Processing Cycle

6.2.1 Linear Algebra as Building Block of AI

Linear algebra is the backbone of artificial intelligence. It is the core language that represents the data and parameters in terms of vectors, matrices, and tensors (Sadudeen, 2025). This enables to express whole AI models compactly through computations involving vector and matrix operations (Rani, 2024).

6.2.2 Vectors and Matrices in Data Processing

In an AI model, the data in the form of text, sound, images, or measurements is represented as a vector. The data items are collected and arranged in the form of a matrix called as data matrix $X \in \mathbb{R}^{m \times n}$ (Singh, 2024).

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

The rows of the matrix X represent the observations and the columns represent the features.

The model parameters are represented by the weight vector $w \in \mathbb{R}^n$.

Thus, a simple linear AI model can be written as $y = Xw + b$ (2)

where X is the data matrix, w is the weight vector, b is the bias vector and y is the output matrix.

These vectors and matrices provide a compact, efficient and precise way of storing and manipulating large amounts of data in AI systems. Stacking up many such transformations help build complex systems like neural networks. The real-world problems deal with data having large number of features, this makes the computations slow. To address this problem, dimensionality reduction is used which represents the data through lesser but meaningful variables thereby preserving the essential information.

The equation of transformation is $z = Ax$ (3)

where x is the original data vector, A is the matrix of transformation and z is the transformed vector. These transformations can rotate, stretch, scale and combine features to make patterns easier to detect.

6.2.3 Role of Probability and Statistics in Learning from Data

AI models learn from data and make inferences and predictions based on the observations. But the real-world data may not always be free from noise. It may contain errors and randomness due to certain natural phenomena. Artificial intelligence needs to work with uncertainty and variability to extract meaningful results from the data. This is where the role of probability and statistics (Venkata Pavan Saish et al., 2025) comes into play. They provide the

mathematical framework to deal with variability in data and make informed predictions.

Probability theory provides tools for quantifying uncertainties. Probabilistic models such as Bayesian inference and Markov models are used by AI systems to represent relationships between variables.

For events A and B with $P(B) > 0$, the conditional probability is given by

$$P(A/B) = \frac{P(A \cap B)}{P(B)} \quad (4)$$

Baye's theorem is stated as $P(A/B) = \frac{P(B/A)P(A)}{P(B)}$ (5)

Here $P(A)$ is the prior probability of event A, $P(B/A)$ is the likelihood probability of event B when event A has already occurred and $P(A/B)$ is the posterior probability.

Thus, Baye's theorem enables the system to learn from the data and improve predictions in accordance with real time data updates (Qu, 2025). It is widely used in medical diagnosis, recommendation systems, pattern recognition, machine learning and speech recognition where decision need improvement with the continuous updates in data.

When a model is trained, it uses probability distributions for estimation and learning the likelihood of different outcomes. The AI system uses concepts like expectation, variance and maximum likelihood principle for estimation to improve their performance on unseen data thereby making them more robust.

AI systems use descriptive statistics (Martha and Nuthana Priya, 2023) for visualizing and summarizing the data. The data collected is analyzed and interpreted to draw conclusions about a population from a sample. Inferential statistics uses regression analysis to forecast relation between variables, confidence intervals to estimate the range of parameters and hypothesis testing to evaluate the assertions about the population (Rajić, 2026). As shown in Figure 6.2, these methods when integrated together support interpretation and decision making to generate meaningful insights.

In machine learning, statistics is used for:

- **Feature Selection:** Identifying the most relevant features for a machine learning model (Tummalapalli and Konakalla, 2025)

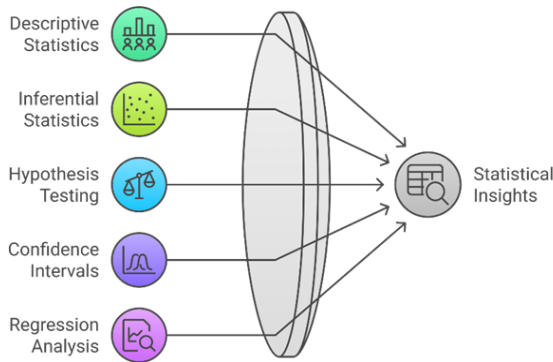


Figure 6.2: Structure of Statistical Analysis

using tests such as t-test and chi-square test to assess the relationship between variables. This reduces the complexity and improves the accuracy of the model.

- **Model Selection:** Choosing the best model by comparing the performance of different algorithms on a validation set (Raschka, 2020).
- **Model Evaluation:** Using metrics like precision, recall and F1 score to assess and quantify the performance of the model on unseen data (Rainio et al., 2024).
- **A/B Testing:** Comparing different versions of the model in real-world scenarios to determine the best performing model (Kohavi et al., 2020).

As illustrated in Figure 6.3, it is necessary to follow a structured approach to ensure that the AI system is accurate on trained data and is reliable and generalizable for real-world applications.

6.2.4 Calculus and Optimization In Training AI Models

Training an AI model requires adjusting its parameters to minimize its errors. Learning algorithms in artificial intelligence are essentially a problem of optimization built on differential calculus (Fernandez et al., 2025). Calculus is crucial for understanding how the changes in model parameters affect the loss function. Vector containing the partial derivatives of a function with respect to each of its variables is called gradient of the function. In training an AI model, the gradient

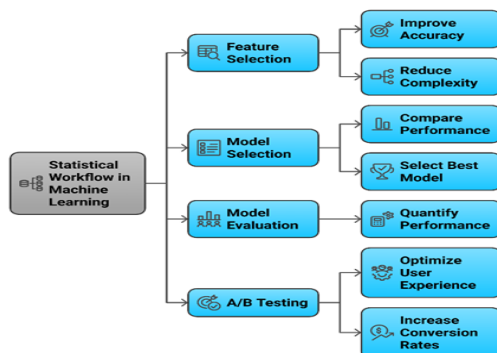


Figure 6.3: Applications of Statistics in Machine Learning Models

of the loss function with respect to the model's parameters indicates the direction of steepest increase of the loss function.

Let L denotes the loss function and $\theta = \{\theta_1, \theta_2, \dots, \theta_n\}$ denotes the set of n parameters, then the gradient is denoted by $\nabla L(\theta) = \left(\frac{\partial L}{\partial \theta_1}, \frac{\partial L}{\partial \theta_2}, \dots, \frac{\partial L}{\partial \theta_n} \right)$ (6)

Therefore, moving opposite to the direction of gradient reduces loss.

Backpropagation is an algorithm used to compute gradients efficiently in a neural network by propagating errors backward using the chain rule. It works in two steps: a forward pass, where the network produces an output and the loss is calculated, and a backward pass, where gradients of the loss with respect to each parameter are computed and used to update the weights and biases. Optimization algorithms are used to determine the minimum of loss function (Michelucci, 2024). They use gradients calculated using backpropagation to update model's parameters and minimize the loss.

However, training AI models using calculus and optimization faces several challenges. The loss functions are usually non-convex in nature with many local minima. The gradients calculated using backpropagation can become either very small or very large known as vanishing or exploding gradients. This can cause instability in the model. Also, the performance of the model depends upon

carefully choosing the appropriate parameters for hyperparameter tuning. This can be computationally expensive and time-consuming process. The optimization process can also cause overfitting of the training data. This may require regularization to improve generalization. Figure 6.4 discusses the strategies required to overcome the challenges while training an artificial intelligence model.

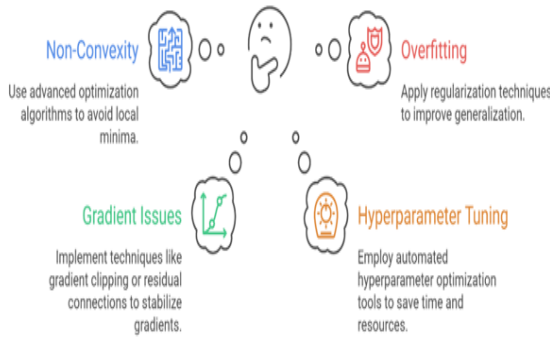


Figure 6.4: Strategies for Overcoming Challenges in AI Model Training

6.2.5 Discrete Mathematics and Logical Structures in AI

Discrete mathematics focuses on set theory, graph theory, logical statements, and combinatorics. These are crucial for problem solving, reasoning and decision making in AI systems (A. Dinesh Kumar and Tawfeeq Abdulameer Hashim Alghazali, 2025).

- **Set Theory:** It is used to represent collection of objects and perform operations like union, intersection, complement etc. on them. Sets group data points with similar characteristics enabling clustering. Thus, AI systems define relationships, perform queries, infer new knowledge and make decisions (Krishna and Aravind, 2025).
- **Graphs, Trees and Networks:** Graphs are used to model connections between objects and states (Khemani et al., 2024). Trees are used in search, decision making, games and, language processing. Bayesian networks combine graph theory and probability to handle uncertainty.

- **Logical Statements:** In AI systems, logic is used for knowledge representation, planning and, problem solving. It is used for building expert systems that imitate the reasoning of human experts in a particular domain (Liu et al., 2022). Propositional logic supports simple reasoning tasks. Predicate logic is useful for complex reasoning and fuzzy logic are used for handling uncertainty (Sherin, 2025).
- **Combinatorics:** Combinatorics deal with counting and arranging objects. In AI systems, it supports probability and statistical analysis by designing efficient algorithms. Combinatorial optimization is used in machine learning for model and feature selection. It also aids natural language processing in analysing and generating sentence structures (Liang, 2025).

The key areas of discrete mathematics in building AI systems as shown in Figure 6.5 are the foundations for analyzing and optimizing algorithms.



Figure 6.5: Key Areas of Discrete Mathematics in AI

6.3 Pedagogical and Scientific Significance of Mathematics In AI

In the AI era, mathematics literacy has become a foundational skill for scientists, wide range of professionals and informed citizens. For the professionals directly involved in building AI systems, mathematical literacy is indispensable (Kumar, 2024). It enables them to understand the principles behind AI algorithms and develop new algorithms and techniques. When an AI system fails, a strong understanding of the underlying mathematics is essential for troubleshooting and

debugging the system. Mathematical knowledge is also important to evaluate the limitations and assess the performance and biases of the AI systems.

For people in the fields using these AI systems, learning basics of mathematics is equally important. It allows them to communicate effectively with the AI systems, and make assessment of the potential benefits and risks involved in using AI. This helps them to effectively use AI in their work and make informed decisions.

AI applications are being increasingly used by common people in daily life. Learning mathematics can help them to develop critical thinking required to understand and implement these technologies. AI is everywhere around them so mathematical literacy is extremely important for them to distinguish between the hype and reality that surrounds AI.

6.4 Conclusion

Artificial intelligence has seen a rapid rise in the past decade. This chapter explored the role of core mathematical concepts essential for the development of AI systems. As AI expands in complexity and in scientific and societal domains, mathematics remains as the primary language to build and understand such systems. Mathematical frameworks are essential to ensure the efficiency, stability and interpretability of the advanced AI models. Thus, developing strong understanding of mathematical concepts is necessary to bridge the gap between theory and application.

References

- [1] Abbasi, A. (2025). Mathematical framing for fair and robust artificial intelligence in corneal biomechanics. *Intelligent Medicine*, 5(4), 331–332. <https://doi.org/10.1016/j.imed.2025.05.005>
- [2] Fernandez, E., Huilcapi, V., Birs, I., and Cajo, R. (2025). The Role of Fractional Calculus in Modern Optimization: A Survey of Algorithms, Applications, and Open Challenges. *Mathematics*, 13(19), 3172. <https://doi.org/10.3390/math13193172>
- [3] Golec, M., Hatay, E. S., Gill, S. S., and Buyya, R. (2025). Artificial Intelligence (AI): Foundations, trends and future directions. *Telematics and Informatics Reports*, 20, 100265. <https://doi.org/10.1016/j.teler.2025.100265>

- [4] Khemani, B., Patil, S., Kotecha, K., and Tanwar, S. (2024). A review of graph neural networks: Concepts, architectures, techniques, challenges, datasets, applications, and future directions. *Journal of Big Data*, 11(1), 18. <https://doi.org/10.1186/s40537-023-00876-4>
- [5] Kohavi, R., Tang, D., and Xu, Y. (2020). Trustworthy Online Controlled Experiments: A Practical Guide to A/B Testing. Cambridge University Press. <https://doi.org/10.1017/9781108653985>
- [6] Krishna, P. V. N., and Aravind, A. S. (2025). The Role of Set Theory in Modern Computing: From Databases to AI. *International Journal of Current Microbiology and Applied Sciences*, 14(8), 253-258. <https://doi.org/10.20546/ijcmas.2025.1408.024>
- [7] Kumar, A. (2024). Mathematics behind artificial intelligence and machine learning. *International Journal of Computing and Artificial Intelligence*, 5(2), 168–172. <https://doi.org/10.33545/27076571.2024.v5.i2b.186>
- [8] Kumar, D., and Alghazali, T. A. H. (2025). The impact of graph theory and network algorithms on AI-enabled digital ecosystems. *International Journal of Scientific Research and Modern Education*, 10(2), 71-85. <https://doi.org/10.5281/ZENODO.17165164>
- [9] Liang, J. (2025). Review of Combinatorial Optimization Methods in the Intelligent Era. Proceedings of the 2025 *International Conference on Software Engineering and Computer Applications*, SECA '25, 128–134. <https://doi.org/10.1145/3747912.3747933>
- [10] Liu, K., Li, Y., and Cui, R. (2022). Design of a Computable Approximate Reasoning Logic System for AI. *Mathematics*, 10(9), 1447. <https://doi.org/10.3390/math10091447>
- [11] Martha, S., and Nuthana Priya, M. (2023). Role of Statistics in Artificial Intelligence. *International Journal of Engineering Applied Sciences and Technology*, 8(1), 96–98. <https://doi.org/10.33564/IJEAST.2023.v07i12.015>
- [12] Michelucci, U. (2024). Calculus and Optimisation for Machine Learning. In U. Michelucci (Ed.), *Fundamental Mathematical Concepts for Machine Learning in Science* (pp. 21–62). Springer International Publishing. https://doi.org/10.1007/978-3-031-56431-4_3
- [13] Qu, B. (2025). Bayes' Theorem in Machine Learning: A Literature Review. *Theoretical and Natural Science*, 86, 26–31. <https://doi.org/10.54254/2753-8818/2025.20329>
- [14] Rainio, O., Teuhio, J., and Klén, R. (2024). Evaluation metrics and statistical tests for machine learning. *Scientific Reports*, 14(1), 6086. <https://doi.org/10.1038/s41598-024-56706-x>

- [15] Rajić, V. (2026). Statistical Hypothesis Testing: A Comprehensive Review of Theory, Methods, and Applications. *Mathematics*, 14(2), 300. <https://doi.org/10.3390/math14020300>
- [16] Rani, M. K. (2024). Linear algebra as the mathematical foundation of artificial intelligence: concepts, applications, and future prospects. *International Journal of Engineering Science and Humanities*, 1(1), 123–137. <https://www.ijesh.com/j/article/view/371>
- [17] Raschka, S. (2020). Model Evaluation, Model Selection, and Algorithm Selection in Machine Learning (ArXiv:1811.12808). arXiv. <https://doi.org/10.48550/arXiv.1811.12808>
- [18] Sadudeen, M. (2025). Linear Algebra as a Mathematical Foundation for Machine Learning Algorithms. *International Journal of Innovative Science and Research Technology*, 2257–2262. <https://doi.org/10.38124/ijisrt/25sep829>
- [19] Sherin, N. (2025). Fuzzy Logic and Set Theory in Artificial Intelligence Decision-Making. *International Journal for Research in Applied Science and Engineering Technology*, 13(5), 1656–1658. <https://doi.org/10.22214/ijraset.2025.70546>
- [20] Singh, R. M. (2024). Mathematical concepts of linear algebra in AI tools: A calculation-based study. *Journal of Hyperstructures*. <https://doi.org/10.22098/jhs.2024.15660.1038>
- [21] Sinha, S., Datta, S., Kumar, R., Bhattacharya, S., Sarkar, A., and Das, K. (2024). Exploring Creativity: The Development and Uses of Generative AI. In *The Pioneering Applications of Generative AI* (pp. 167–198). IGI Global Scientific Publishing. <https://doi.org/10.4018/979-8-3693-3278-8.ch008>
- [22] Tummalapalli, V., and Konakalla, K. (2025). Statistical Techniques for feature selection in Machine learning Models. *IJIRMPS - International Journal of Innovative Research in Engineering and Multidisciplinary Physical Sciences*, 13(3). <https://doi.org/10.37082/IJIRMPS.v13.i3.232566>
- [23] Venkata Pavan Saish, N., Jayashree, J., and Vijayashree, J. (2025). Mathematical Foundations and Applications of Generative AI Models. In N. R. Vajjhala, S. S. Roy, B. Taşçı, and M. E. Hoque Chowdhury (Eds.), *Generative Artificial Intelligence (AI) Approaches for Industrial Applications* (pp. 19–45). Springer Nature, Switzerland. https://doi.org/10.1007/978-3-031-76710-4_2

Chapter 7

AI IN MATHEMATICS AS A TOOL TO SOLVE PROBLEMS

Tanya

Assistant Professor, P. G. Department of Mathematics, Khalsa college for Women, Civil Lines, Ludhiana, Punjab, India-141001.

Email: tanyataneja221@gmail.com

Abstract

Artificial Intelligence (AI) is transforming mathematics by automating theorem proving, enhancing computational efficiency and drawing patterns in mathematical structures. AI-powered tools, such as machine learning algorithms and symbolic computation systems, make researchers capable of solving complex problems, verifying proofs, and generating graphs of an equation. These advancements speed up the mathematical discovery and reduce human error in research. This study will combine AI technology to construct a corresponding mathematical map to optimize the teaching path. Beyond research, AI improves mathematical education by providing customized learning and tutoring. AI systematically introduces the construction process of a mathematical knowledge graph from the levels of mathematical content extraction, integration, and processing; visualization and display; and puts forward an effective program based on the knowledge graph. It also plays a crucial role in applied mathematics like calculus, algebra, and differential equations, also optimizing solutions in cryptography, physics, and engineering. However, challenges persist, including ethical concerns regarding AI's role in creativity. It provides optimal solutions for complex problems, from resource allocation to shortest path, which are far quicker than traditional methods. Moreover, we explore the connection between theoretical concepts and practical use, illustrating how

mathematics fosters modern AI technologies. AI creates diagrams, flowcharts, and simulations for probability, calculus, and geometry, making abstract math tangible.

Keywords: Calculus, Linear Algebra, Optimization, Problem Solving, Theorem Proving

7.1 Introduction

Traditionally, mathematics has relied on manual computations, abstract reasoning, and deductive processes to explore new theories and to solve complex problems. AI has introduced revolutionary methods that are reshaping mathematical research and problem-solving. AI-powered tools such as automated theorem provers and symbolic computational systems (Mishra et al., 2023) are a few examples. One of AI's most significant contributions to mathematics is its role in theorem proving and solving the problems graphically. With AI we are now able to get solutions to complex equations, integration, and differential equations efficiently and in an easy way. Beyond theoretical advancements, AI has practical applications in mathematical education and industry (Nitin, 2023). This chapter analyzes the role of AI in theorem proving and problem solving, mathematical education and learning, computational mathematics, and optimization. The chapter also emphasizes AI-assisted optimal solutions for complex problems and connections between theoretical concepts and practical use by creating flowcharts, diagrams, and simulations for probability, calculus, and geometry, making abstract math tangible (Namrata, 2025).

7.2 The Relationship Between Mathematical Principles And AI

All fields related to AI are based on the solid foundation of mathematics. The center of the AI revolution is built on a complex web of fields, all rooted in mathematics. To understand why mathematics is so important to AI, we first need to understand the basic concepts behind AI itself to fully appreciate the significance of math in AI research (Popade, 2025).

The architecture of neural networks, the fundamental units of deep learning, requires a solid understanding of linear algebra. Neural

networks use matrices and vectors to encode and manipulate data. An essential component in optimizing AI models is calculus. Calculus is used in methods like gradient descent and back propagation to reduce mistakes and modify the parameters of machine learning models. Artificial intelligence (AI) systems can learn from data and keep getting better at what they do thanks to certain mathematical principles (Almuhur, 2024).

In artificial intelligence, probability theory and statistics are essential for tasks like computer vision, natural language processing and decision-making. The mathematical foundation for calculating uncertainty, analyzing data and formulating probabilistic predictions is provided by probability distributions, Bayesian inference, and hypothesis testing (Almuhur, 2024).

7.3 Methodology of Artificial Intelligence

The main idea is to create systems that can perform tasks that typically require human intelligence, such as reasoning, learning, problem-solving, and decision-making. AI methods can be broadly categorized into three types: symbolic AI, machine learning, and evolutionary computation (Murphy, 2012). There are 7 stages of AI that describe its evolution from simple programs to hypothetical superintelligence, generally moving from rule-based systems to contextual awareness, then domain-specific expertise, followed by reasoning machines, progressing towards artificial general intelligence (AGI), then artificial superintelligence (ASI) that surpasses humans, culminating in a singularity where AI merges with or transcends human capability, radically changing existence. These stages represent increasing autonomy, understanding, and cognitive power (Powell, 2024).

7.4 Problem Solving And Equation Generation

One significant area where AI is transforming mathematics is in automated problem-solving and equation generation. AI models, particularly symbolic computation systems, pattern recognition and neural networks, are now capable of solving complex equations, generating new mathematical problems, and even suggesting alternative solutions (Powell, 2024). This is particularly useful in calculus, algebra and differential equations, where AI can analyze patterns and derive

solutions faster than traditional methods (Bishop, 2006). Consider the differential equation:

$$\frac{dy}{dx} = 1 - y^2, y(0) = 0$$

(Autonomous equation)

AI-based symbolic computation tools like Wolfram Alpha, Mathematica and MATLAB can solve this differential equation efficiently using the variable separable method (www.wolframcloud.com).

Solution: $\frac{y-1}{y+1} = -e^{-2x}$

AI-driven systems recognize patterns and apply the correct techniques without manual intervention, making them useful for students and researchers alike.

Also results with a hyperbolic curve in the Wolfram Cloud.

In Wolfram Alpha we can also trace the curves, which convert theoretical equations to graphical representation.

7.5 Calculus

Calculus allows AI by enabling algorithms to optimize their performance using methods such as optimization techniques. By calculus, AI can adapt model parameters to reduce errors, thus improving the accuracy and performance. It also helps to enhance the results by refining the performance of the model and thus plays an important role in artificial intelligence (AI). It also plays a vital role in optimization by analyzing the convexity of loss functions. A function is considered convex if its second derivative is positive, indicating that the function has no local maxima. AI models, especially neural networks, use derivatives to find the minimum point of a cost function, which minimizes errors and maximizes performance (Popade, 2025).

- **Multivariable Calculus:** Essential for dealing with complex, high-dimensional data, helping models understand gradients and optimize across many parameters (Popade, 2025).
- **Modeling Change:** Differential calculus allows AI to analyze, predict, and react to changing data points in real-time.
- **Optimization:** It is a process of improving artificial models and algorithms to enhance accuracy, speed and efficiency while reducing resource consumption. It involves refining

data, adjusting parameters and adapting to AI driven search to ensure higher performance, faster and better visibility (Rojas, 1996).

7.6 Linear Algebra

The main focus of linear algebra is to study vectors, matrices and linear transformations, all of which are essential for representing the data. It often deals with large datasets also offers the necessary and sufficient data for transformation (Lay et al., 2009)

- **Data Representation:** Data is structured as vectors (features) and matrices (datasets). For instance, images are treated as matrices of pixel intensities, and text is converted into high-dimensional vectors (Popade, 2025).
- **Neural Networks:** Deep learning models rely on matrix operations to process data. Each layer applies linear transformations to inputs, adjusting weights during training via backpropagation (Rojas, 1996)
- **Dimensionality Reduction (PCA):** Principal Component Analysis uses eigenvalues and eigenvectors to simplify complex datasets while preserving maximum variance, enhancing computational efficiency (Castelvecchi, 2024).
- **Recommendation Systems and Data Analysis:** Techniques like Singular Value Decomposition (SVD) break down matrices to uncover hidden patterns, used in clustering and recommendation engines (Lay et al., 2009).
- **Performance:** It helps optimize models, reducing complexity for faster training and better accuracy.

7.7 Theorem Proving

- It is a branch of automated reasoning that uses computer algorithms to verify, construct, or discover formal theoretical proofs using axioms and inference rules. It combines symbolic logic with modern machine learning to automate complex tasks in mathematics and software verification. For example:
 - automated theorem provers (fully automatic), interactive theorem provers (human-guided), and hybrid systems (Tao et al., 2022).

- Optimization: It identifies and fixes the error automatically to improve the effectiveness and efficiency of these systems (Tao et al., 2022).
- Automated process: It is an automated process that is faster and more efficient than manual methods (Tao et al., 2022).

7.8 Conclusion

Artificial intelligence has emerged as a transformative force in mathematics, theorem proving, and problem solving. By automated proofs and graphs of equations to solve complex problems and reducing error by optimization, AI works as a powerful tool to solve the problems graphically and theoretically and also enhances the teaching and learning techniques. It also saves time by providing proofs of the theorems. By leveraging mathematical principles like linear algebra, calculus, optimization, and graph theory, AI is able to represent the large datasets and provide maximum convexity and visual representation of the equations.

References

- [1] Almuhr, E. (2024) Artificial intelligence in mathematics. *ISRG Journal of Modern Science*, 10. <https://doi.org/10.5281/zenodo.13673839>
- [2] Bishop, C. M. (2006). *Pattern Recognition and Machine Learning*. Springer, New York.
- [3] Castelvechi, D. (2024). DeepMind AI hits milestone in solving maths problems. *Nature*, 632, 8. <https://doi.org/10.1038/d41586-024-02441-2>
- [4] Lay, D. C., Lay, S. R., and McDonald, J. J. (2009). *Linear Algebra and Its Applications* (5th ed.). Pearson.
- [5] Mishra, C., Moulik, S. R., and Sarkar, R. (2023). Mathematical conjecture generation using machine intelligence. *arXiv preprint arXiv:2306.07277*. <https://doi.org/10.48550/arXiv.2306.07277>
- [6] Murphy, K. P. (2012). *Machine Learning: A Probabilistic Perspective*. MIT Press, Cambridge, Massachusetts.
- [7] Namrata, G. P. R. (2025). The Influence of Artificial Intelligence in Mathematics: Progress, Applications, and Future Opportunities. *International Journal of Latest Technology in Engineering, Management and Applied Science*, 14(3), 387-391. <https://doi.org/10.51583/IJL-TEMAS.2025.140300042>
- [8] Nitin, R. (2023). Enhancing Mathematical Capabilities through ChatGPT and Similar Generative Artificial Intelligence: Roles and Challenges in Solving Mathematical Problems, 6 <http://dx.doi.org/10.2139/ssrn.4603237>

-
- [9] Popade, S. M. (2025). The Role of Mathematics in Artificial Intelligence. *International Journal of Scientific Research in Science and Technology (IJSRST)*, 12(8), 303–308. <https://doi.org/10.32628/IJSRST>
 - [10] Powell, W. (2024). The 7 Levels of AI, Their Evolution, and Their Role in Trucking and Transportation. <https://tinyurl.com/7levelsofAISpanish>
 - [11] Rojas, R. (1996). *Neural Networks: A Systematic Introduction*. Springer, New York.
 - [12] Tao. T., and DeepMind Research Team (2022). Neural Networks in Number Theory. *Journal of Mathematical Analysis*, 20(3), 143–159.
 - [13] Wolfram, S., and Bauer, A. (2023). AI-Driven Symbolic Computation. *Computational Mathematics Journal*, 18(2), 67–84.

NOTES

This image shows a single sheet of white paper with horizontal ruling lines. The lines are evenly spaced and run across the width of the page. There are no margins, text, or other markings on the paper.

Chapter 8

ARTIFICIAL INTELLIGENCE AND LITERATURE: TRANSFORMATIONS, CHALLENGES AND FUTURE

Anshu

Assistant Professor, Department of English, Khalsa College for Women,
Civil Lines, Ludhiana, Punjab, India-141001.

Email: anshugoel1177@gmail.com

Abstract

This chapter is going to deal with how language and technology are interdependent on each other. The technology has helped in evolving and flourishing the literature. With the setting up of the first printing press, the people were able to preserve the literature that was earlier transmitted orally from one generation to another. Gradually the means of printing developed, resulting in the widespread circulation of the literature, making it accessible for a large number of people to study. With the invention of the computer, it becomes easier to get the text published and further the invention of artificial intelligence (AI). There is a boom in the creation and spreading of the literature. In this chapter, the relationship between literature and AI will be dealt with. It will also cover the challenges that AI has created for the writers and what the future of literature will be in AI times. The focus will also be on whether AI is going to help in teaching pedagogy or not. If yes, then to what extent? It will also deal with ethical issues and cultural concerns, focusing on copyright issues as well.

Keywords: AI, Teaching Pedagogy, Literature, Copyright, Ethical Issues

8.1 Introduction

The development of literature throughout history has been bound by the development of communication technology, a process that has created a synergistic partnership between the two, defining a new realm of possibility for humanity in expressing itself. The media through which we embody our thoughts in writing, print, typing, and digital interface—define the contours of the cognitive experience of the literary act (Hayles, 2002). The history of literature has undergone great changes along with each era of new technology, where the advent of the printing press from an age of oral tradition and then again with the advent of digital technology has brought about the creation of nonlinear literature. But the rise of the latest technology, AI and large language models, marks a clear departure from such antecedents in the form of what is described as a “paradigmatic shift” in creative discourse.

Whereas prior innovations in technology functioned only as extensions—inventions that enhanced human abilities in terms of speeding up dissemination or extending its range—AI represents an independent entity within the process of creation. Such a fact is of utmost importance when considering how modern AI programs are capable of producing highly sophisticated language devoid of human input at all stages. As computer-based literary scholars have observed, the presence of generative AI implies that “literature is not solely the domain of the human mind, but rather a space of collaboration—or competition—between algorithm and author” (Boden, 2004).

The core of this issue undermines the foundational principles on which literature stands: experience and authorship. The capacity of a machine to generate a substantial amount of data to craft a work of art that triggers an aesthetic and emotional response challenges the anthropocentric conception of literary significance. The increasing reliance on autonomous systems calls for a reevaluation of the “ontological status of creativity,” since we have reached a point wherein the “mechanical mimicry of human cognition comes to imitate the very mechanisms that were once at the heart of our distinct creative capacity” (Floridi, 2019). In effect, the incorporation of artificial intelligence into literature implies not only the use of another form of narration but also the questioning of the concepts of authorship and significance.

Incorporating AI into the humanities signifies a monumental shift in our perception of creative processes and methods of research. No longer serving as passive aids or simple observers, AI technologies have crossed boundaries between merely being used as tools and participating actively in creating complex literary genres, such as poetry, novels, theater plays, and critical reviews. The emergence of distant reading, advocated by Franco Moretti, along with techniques such as sentiment analysis and natural language processing (NLP), also signifies a significant shift in the study of literature. According to Franco Moretti, “The trouble with close reading is that it necessarily depends on an extremely small canon”, and, indeed, through AI-enabled technologies, we have managed to overcome this obstacle and conduct research on literary works that are out of reach for the human mind (Moretti, 2013).

The current chapter discusses the complexity of interaction between AI technologies and literature and the necessity to critically analyze the relationships between creative activity, scientific approaches, ethical issues, and emerging concepts. On the one hand, the capacity of large language models (LLMs) to reproduce human syntactic and narratological skills is impressive, yet, at the same time, there is a need to differentiate between machine learning mechanisms and human intentionality. Referring to the concept of “technogenesis,” which presupposes that “human and machine are not two discrete things, but a single hybrid” (Hayles, 2005), it can be assumed that AI should not be interpreted simply as an instrument used to replicate the creative process performed by humans. In fact, it can become a change agent in literary practice due to its ability to challenge traditional literary theories and create conditions for dialogue between the human subject and algorithmic results.

8.2 Technology and The Evolution of Literature

The history of literature has inevitably been inextricably linked to various technological advancements, which have, in every instance, served as the catalyst that continues to redefine the way literature is produced, disseminated, and consumed, as well as the way it is preserved and interpreted over time (McLuhan, 1964). The interrelation between literature and technology can be conceptualized as far back as the earliest form of articulated and codified communication, including cuneiform inscriptions,

hieroglyphics, and scrolls inscribed on papyrus, which inevitably had an impact on literature in terms of the limitations and opportunities that they presented. The codex, which was advanced in late antiquity, not only significantly perfected the reading process to facilitate the reading and storage of complex literature but also served as the precursor to the modern-day book (Ong, 1982).

The most revolutionary advancement in the whole course of literary evolution, however, was arguably achieved through the discovery of the movable-type printing press by Johannes Gutenberg around the mid-15th century. The latter democratized knowledge breaking the hegemony of the literate classes, and achieving unprecedented levels of text proliferation. Religious texts such as the Gutenberg Bible and the proliferation of secular literature helped to launch the Renaissance, the Reformation, and the Enlightenment. It also gave birth to standardized languages, the concept of authorship as a profession, and the creation of a range of new literary forms to meet the burgeoning reading public, such as the novel (Woodward, 1980).

As industrialization advanced, so did advancements in printing technology. The 19th century also introduced steam-powered presses and mass production, making books and periodicals even cheaper. Literature became an integral part of life, and this can be attributed to serial publications within newspapers and periodicals, especially fiction writing, which became popular among the middle and working classes. Writings such as those done by Charles Dickens are attributed to his episodic writings, which made him popular and famous, thus creating a new kind of narrative style altogether.

The 20th century introduced even greater transformations with the rise of radio, film, and television media that re-imagined narrative forms and brought literature into auditory and visual realms. Literary works were adapted for broadcast and screen, allowing stories to reach audiences who might never have picked up a book. Meanwhile, technologies like the typewriter and word processor changed the very process of composing writing, making it possible to draft more quickly, edit with ease, and play with form and style in new ways (Kirschenbaum, 2008).

In the modern digital world, however, the rate of evolution in publishing in general, and literature in particular, has picked up speed. Publishing in the digital era, for example, can be argued to

have altered the traditional publishing process, thanks to the internet and platforms such as Amazon Kindle. E-books, for example, have offered diverse reading options for literature, considering diverse learning needs. Hypertext fiction and interactive stories, akin to those in video games or interactive choose-your-own-adventure apps, subvert the idea of linear storytelling and allow readers to participate in the story.

The latest example in this chain is the advent of artificial intelligence, which is already changing the very essence of what is meant by “authorship”. This is a technology not just capable of crafting poetry, outlining stories, or replicating the style of a celebrated literary master but increasingly forcing a serious re-evaluation of the very notion of creativity, originality, and human contribution to the creative process itself. While perceived by some to be a threat to literary authenticity, there are certainly signs of its potential to be a useful ally to writers.

Ultimately, each technological advance not only increases the availability of literature but also changes the form, practice, and possibility of literature itself. From the chisel to the press, from the typewriter to the algorithm, technology remains instrumental to the creation, conveyance, and consumption of literature—keeping the art form very much living, breathing, and tied to the technology of the age.

8.2.1 The Printing Press and the Democratization of Literacy

The invention of the printing press in the 15th century by Johannes Gutenberg marked a seismic shift in the history of literature. Prior to its invention, texts were painfully copied out by hand, and this greatly limited literacy to religious institutions, the elite of that time, and monastic scribes. The printing press mechanized the reproduction of books, which lowered costs and allowed mass production. This revolutionized access to knowledge, fostering the spread of vernacular languages and encouraging the standardization of grammar, syntax, and literary conventions. The coincidence of this technological leap with the Renaissance, the Reformation, and the rise of the novel—for example, Cervantes' *Don Quixote* (1605) and serialized novels by Dickens—are possible only in printed form. The press catalyzed, finally, the global exchange of ideas, as translated

works and printed pamphlets began to circulate across Europe, laying the ground for modern literary traditions (Raj and Bansal, 2024).

8.2.2 Typewriters and the Mechanization of Creativity

The 19th century witnessed a new tool geared to revolutionize writing itself: the typewriter. The pens and paper traditionally used by writers were inadequate for making changes. However, with the development and use of typewriters, writers like Jack London and Virginia Woolf succeeded in using this technology for a new kind of editorial exactness. With typewriters, they also had the ability to produce many drafts, allowing them to submit work to editors. The typewriter also opened new avenues because writers from all walks of life were able to use this tool without incurring any expenses. This was a time when modernist techniques began to take center stage in literature. The stream-of-consciousness narrative, fragmented forms, and self-searching writing suggest that the typewriter's mechanical discipline may have informed the formal innovation of this era (Jenkins, 2018).

8.2.3 Word Processors and the Digital Revolution

The 20th century saw the introduction of word processors, which further changed literature production. Programs such as WordPerfect and Microsoft Word were designed for effortless production, editing, and collaboration, allowing for experimental and creative freedom for authors. It is also important to notice that there was a shift from the physicality of literature creation, allowing for a more flexible process. In addition, genres such as “book scan” and Internet collaborations were also introduced during this period, such as in Internet forums, such as Clubhouse or Wattpad (Haigh, 2006).

8.2.4 Digital Technologies and the Redefinition of Literary Form

The 21st century has been marked by the most revolutionary change so far, for digital technologies have not only reshaped the way literature is created but also its very definition. The genre of “hypertext fiction”, which is the term given to interactive fiction and offers the possibility of exploring non-linear paths of storytelling, was born in the 1990s. The best examples of this are “Afternoon: a story” by Michael Joyce (1990) and “Patchwork Girl” by Shelley

Jackson (1995). Electronic literature (or e-lit) has evolved to include everything from procedural poetry, which is capable of producing new forms every time it is read, to multimedia fiction, which may include combinations of text, sound, and video (Herbert, 2015).

Simultaneously, digital platform presence across the world, including blogs, social media sites, and Substack sites, has streamlined the process and enabled content creators to directly target their audiences.

8.3 AI and Literary Creation

Today, through AI machines, poems, short stories, novels, and dramatic dialogues can be generated with remarkable fluency. Their mode of functioning is based on probabilistic prediction, selecting words based on patterns learned from texts that already exist. Currently, writers make use of AI as a creative assistant.

This type of collaboration has changed the way literature is written. Rather than being written purely out of inspiration, literature is now written as a form of dialogue between humans and algorithms. While critics claim that literature written using such algorithms is unoriginal, proponents of using such algorithms argue that, as Franco Moretti states, all literature is written using cultural mashups, anyway (Moretti, 2013).

8.4 Authorship And Originality

When literature is created through AI, the issue becomes the traditional notion of authorship. This issue brings about the traditional notion that it is part of human agency and intention. However, if literature is created based on a prompt by an AI system, then the notion of authorship becomes shared by programmers and humans. This kind of shared cognition reflects the post human world in general (Hayles, 2002).

This evolution threatens current copyright systems and calls into question issues of originality. In a sense, when an AI produces a poetry piece in the style of Shakespeare, do we consider it an imitation, homage, or an act of plagiarism?

8.5 Computational Literary Analysis

AI has significantly impacted the domain of literary criticism, as a new array of tools can potentially analyze larger chunks of literature than what was possible earlier. Conventional techniques that literary critics have applied to understand literary works include close readings, examining a literary piece or a finite number of works and exploring their content, phenomena, and contextual environments. While this method has its merit, its effectiveness can never be limitless. By bringing in AI tools, scholars can extend their horizons much beyond the confines of a single piece and analyze an enormous volume of literature, ranging across centuries, genres, and geographical locations. By using AI tools, scholars can embrace a new way of exploring macro-level phenomena that may not have come to light while using conventional tools, such as the evolution of narrative forms, an expansion of specific narrative motifs in diverse geographical spaces, and concepts that are embedded in literature by default. AI tools have also provided scholars with the facility of distant reading, a convention that evolved (Moretti, 2016). As a result, AI not only enhances the depth and breadth of literary scholarship but also opens up new avenues for interdisciplinary research, connecting literature with data science, history, and sociology. This technological evolution is reshaping how we understand literature, offering fresh perspectives on authorship, genre, and the cultural forces that shape literary production (Tenen, 2018).

8.6 Distant Reading And Text Mining

In terms of message, the world of literary study, as outlined by Franco Moretti in his notion of “distant reading,” is one in which, as he suggests, “a new perspective is needed to step back from close reading and begin to consider literature as a whole, as a vast, collective system. Close reading, while a powerful tool for understanding the intricacies of any one novel or poem, can never truly allow us to understand literature as an entirety, due to its inherently limited nature. We can only close-read a tiny portion of the millions of texted tomes that have ever been written, but distant reading, by using computer-based methods to process massive libraries, allows us to “focus on units that are much smaller or much larger than the text: devices, themes, tropes—or genres and systems” (Moretti, 2013).

The engine powering this new form of analysis is AI, particularly the field of natural language processing (NLP). Indeed, AI-powered tools are capable of digging through colossal bodies of writing, such as the entirety of Project Gutenberg's digital library, in a matter of hours. They can automatically identify and quantify a variety of phenomena. For example, they can graphically represent the way in which recurring motifs have appeared throughout history by charting the per capita occurrences of particular words or concepts throughout the centuries. They can similarly chart the evolution of genres by using algorithms that key in on the various formal and thematic touchstones that define a particular genre, then charting the rise and fall of that genre in the world of literature (Chan and Colloton, 2024). Finally, they can perform a variety of analyses related to a work's style, a field of study that scholars refer to as 'stylometry,' in order to chart broad stylistic movements that have come to define movements in literature, such as a departure from the long and complicated sentences that defined Victorian-era writing in favor of the concise and simple sentences of the Modernist movement.

Most importantly, such "distant" approaches are not offered as a replacement for traditional "close" approaches but as a way of complementing and expanding them. One should think of "distant" approaches as drawing a detailed, nuanced, intricate, and precise map of a whole continent, while "close" approaches are a detailed, immersive, and nuanced exploration of a single city on this new map. A macro-perspective may reveal an anomaly—a sudden influx of sentimental language in 1920s war literature, an unknown genre that was wildly popular for a short time. These findings usually prompt a new and pressing series of questions for the humanist critic. For instance, the "distant" reading may discover a phenomenon, and the critic is encouraged to engage again with a few specific texts but with a new series of questions: Why is this happening here? What do such specific examples reveal about this phenomenon? Quantitative and traditional approaches engage each other in a dialectical relationship, with the "distant" approach offering context and hypotheses and the "close" approach offering depth, meaning, and explication.

What this methodology can do best, of course, is to put literature into series with the greater cultural and historical systems that produced it. Treating the literary archive as a complex cultural dataset, we can track an intuition about the intricate feedback loop

between art and society. A distant reading of the novels of the 19th century may reveal how metaphors shift from mechanical to biological, reflecting scientific discoveries of the time. The analysis of thousands of travelogues may map the changing anxieties and attitudes of a colonial power across centuries. If we step back, instead of seeing only a few threads, we see the whole tapestry. We get a more dynamic and materialist understanding of literature, moving away from the notion of static, timeless masterpieces toward an ecosystem that is constantly in motion, changing with the world around it (Jockers, 2013).

8.7 Sentiment And Stylistic Analysis

The field of literary narrative analysis is also being transformed with AI techniques that are able to identify the trends in emotion and narrative description through the assistance of advanced sentiment analysis techniques. These technologies have the capability to interpret the dynamic features of emotion using natural language processing algorithms that are able to decode the multiple layers of emotion within texts. For example, AI techniques are able to identify the trends in narrative texts where the story changes from melancholy to hope or anxiety to release using natural language processing algorithms that are able to analyze the narrative across the passage. Furthermore, these are also an integral feature in natural language processing techniques that are able to analyze the style in literature using features such as lexical diversity and complexity. For example, stylistic features are able to analyze the usage of words within texts and assess the complexity in terms of linguistic features such as the length of words or grammatical complexity (Begos, 2024).

Digital humanist Ted Underwood, for instance, highlights the importance of such computational methodologies as providing literary studies scholars with “the freedom to move away from purely speculative hypotheses of literary evolution” and base our analysis on a massive amount of evidence. With such massive amounts of text data—ranging from traditional classics to marginalized texts—even literary studies scholars can examine the influence of historical, cultural, and/or editorial changes on the development of literary canons by applying methodologies such as sentiment analysis, wherein a specific corpus may reveal, for instance, the rise of emotional realism as a dominant motif in 19th-century novels,

reflecting social change, or stylistic analysis, wherein a specific corpus may illustrate the work of literary modernists such as Woolf or Joyce as they deliberately flouted traditional narrative structures. Accordingly, Underwood emphasizes that “these methods not only confirm pre-existing theories on genre development, but they also uncover new patterns that have never been noticed before, such as the evolution of diverse narrative voices in postcolonial literature or the homogenization of styles typical of genre fiction”. All of this, clearly, democratizes scholarship on literature, allowing hypotheses to be put to “wide-scale data sets” and encouraging interdisciplinary discussions that involve literature, computer science, and cultural studies. “No longer”, as Underwood argues, “must literary study remain beholden to hermeneutic vagueness, as a new empirical approach awaits with unprecedented precision” (Underwood, 2019).

8.8 Visualization And Network Analysis

The impact of AI on the study of literature and cultural texts is revolutionary because it now becomes possible to design complex visual tools that allow us to analyze complex relationships within and between cultural texts. Generally speaking, AI has helped us find new ways to visualize complex information because it converts complex information into dynamic and interactive visualizations. For example, a character network analysis technique assists individuals with analyzing dialogues, interactions, and narrative structures within a work of literature because it creates a graph where it is possible for individuals to identify relationships between relevant characters within a given literary work. Within a work like *Les Misérables*, written by Victor Hugo, or *Beloved*, written by Toni Morrison, the relevance of a character network analysis would include identifying primary characters and analyzing relationships that change within the narrative (Livingston, 2025).

By contrast, thematic clustering tools deploy NLP and machine learning to discover repeated motifs, rhetorical patterns, or ideological currents within or across a corpus of texts. These tools allow researchers to trace, within a single work or across an author's oeuvre—or even across genres and historical periods—the evolution of themes such as “justice,” “memory,” or “identity,” clustering together passages or sections that use similar language or imagery. For instance, comparing the thematic clusters in Shakespeare's

tragedies to those in modern plays might reveal resonances between the manner in which different eras negotiate existential despair or moral indistinctness (Fitkov-Norris and Kocheva, 2023).

Intertextual relationship visualizations also extend analysis to the next level by mapping relationships among works, authors, or literary traditions. AI can detect echoes, allusions, or influences by cross-referencing linguistic patterns, plot structures, or narrative techniques. Such a tool would be used by a scholar investigating how Dante's *Divine Comedy* has influenced contemporary fantasy literature to point out metaphors, symbolic systems, or narrative archetypes that are in common and show how classical texts shape modern storytelling (Poibeau, 2025).

More than merely simplifying complex data, such visualizations act as intellectual prosthetics, enabling researchers to “see” patterns entirely imperceptible through close reading alone. Making invisible connections visible, AI tools democratize critical methodologies so that neophytes might appreciate structural nuances of texts while experts test hypotheses at scale. The same digital humanist working through thousands of 19th-century British novels might use these tools to discover underexplored trends in character development or in the evolution of themes that challenge reductive periodization or canonical hierarchies (Livingston, 2025).

Besides this, the inclusion of AI in the humanities also encourages collaboration between different fields as computational elements are combined with traditional hermeneutics. For example, researchers are able to ask new kinds of questions—spanning centuries, cultures, or media formats—on topics such as how internet culture affects viral stories or how the lasting effects of trauma are represented in global literature by utilizing visualizations that combine large amounts of data. This combination of new kinds of technology with traditional textual analysis not just enhances hermeneutic approaches but also fundamentally changes the way humanities scholars think about the inventory of their work.

8.9 Ethical Issues And Cultural Concerns

The integration of AI into literature raises following significant ethical questions:

8.9.1 Creativity and Authenticity

Among a host of issues is that of welfare, a key concern being whether creative texts produced by AI measure up to the criterion of creativity. Is there true creativity without any subjective experience? Creativity is said to be achieved by creating new combinations within a given limit.

8.9.2 Copyright and Data Ethics

When AIs are pre-trained with large data sets, some of these data sets are copyrighted. The legality of this process raises issues of consent, intellectual property, and fair use. The law has not yet recognized whether AI-generated content is an act of infringement or a transformation.

8.10 AI in Literary Pedagogy

The integration of AI in literature classrooms is shaping a new pedagogy in literature, and this concept, while both an opportunity and a threat, guarantees a whole new ball game for both teachers and students in the field. Thirdly, the AI concept in literature studies entails the use of intelligent tutoring tools, a concept that can penetrate the study of literature and aid in the breakdown and interpretation of literature. Especially, the intelligent tutoring platforms apply a combination of the best algorithms in natural language processing, and in this context, they can help in breaking down Shakespearean news and ideologies in *Macbeth*, relate and connect various feminist ideologies in *The Awakening*, and connect and relate various postcolonial ideologies in *Things Fall Apart*.

However, while AI increases accessibility and efficiency, educators have a crucial role to play: to ensure students develop robust digital literacy skills to navigate the limitations and inherent biases of the tool. AI tools are frequently reliant on training data derived from either historical or Western-centric corpora, which tends to champion Eurocentric or culturally narrow interpretations. For instance, an AI may poorly contextualize the nuances within Indigenous storytelling in Chinua Achebe's works or completely misunderstand the socio-political underpinning of modernist poetry such as Eliot's *The Waste Land*. Educators need to guide students in interrogating these outputs through questions such as "Whose

voices are prioritized in this summary?” or “How might this AI’s training data shape its thematic analysis?” In developing this kind of critical interrogation, teachers encourage students to understand that AI-generated interpretations are neither neutral nor infallible but are, instead, reflective of the algorithms and data constituting their making (Jain, 2025).

Additionally, a student’s ability to evaluate AI’s insights can be a crucial learning tool in developing analytical skills. By providing a student with the choice to compare AI’s “themes” with his or her own opinions and theories, a teacher is allowing the student to think in a metacognitive direction, as this can help him better recognize ideas and concepts. Consider, for example, a summary from an AI tool identifying a piece of fiction’s ‘main conflict’ without mentioning any underlying tensions that a human reader might recognize. By allowing a student to recognize these aspects, a teacher can enhance his ability to think critically and make arguments based on evidence, a skill that is essential in any academic and professional life.

Importantly, AI should not be considered a replacement for human-led literary education but rather a dynamic supplement to it. When thoughtfully integrated, AI can amplify classroom discussions by automating time-consuming tasks of compilation, such as building a timeline of historical context or creating annotated texts. For example, a teacher might ask an AI to produce a draft summary of the themes in *The Catcher in the Rye* and then use class time to debate Holden Caulfield’s psychological state or the novel’s cultural legacy. AI can also democratize access to advanced analytics for students with disabilities, language barriers, or different learning styles through multilingual support, visual aids, or interactive study plans tailored to individual needs.

Ultimately, it’s about creating a literate society, aptly positioned to thrive in a digital world. As educators link AI’s computational capacities with human critical insight, they better position their students to be knowledgeable consumers and discerning producers of literary discourse. The balance will ensure that no matter how rapidly technology changes, the heart and soul of literary education—empathy, critical analysis, and cultural awareness—remain intact. Rather than fearing its incursion, AI’s potential can be tapped by the teacher to open new lines of discussion, foster curiosity, and allow students to

better negotiate the complex nature of the evolving literary landscape (Lanigan, 2025).

8.11 Theoretical Perspectives

AI and literature interface well with several theoretical approaches, which question the conventional understandings of creativity, meaning, or cultural mediation. Consequently, posthumanism, as a theoretical framework, challenges the anthropocentric positions traditionally prevalent in creativity. According to N. Katherine Hayles, the introduction of a posthuman perspective, which presents the emergence of intelligence as a “distributed phenomenon among agents as much a product of their entanglement as a property of any agent individually,” repositions the role of the human element in the production or creation of art, literature, or any other forms of cultural solution or mediation. For instance, when AI systems code or “co-author” a literary piece, instead of simply resorting to or copying the characteristics of the human author, there is an emergence of “non-human patterns.” This, according to Hayles, leads us to consider the “question of the status of authorship or the text itself, which might be seen as a ‘cyborg’ entity inseparable from its computational context. A posthuman perspective thus challenges the anthropocentric positions traditionally prevalent in creativity (Hayles, 2002).

Deconstructive theory, which emphasizes the Derridean concept of binary oppositions, the instability of meaning, and the futility that arises in trying to find meaning in language, seems to have an uncanny similarity with the algorithms associated with the generation of texts through AI. This is because the futility that Derrida described seems to be implicit in the “play of signifiers” that the text generated through a generative adversarial network or a transformer such as GPT-3 follows. Furthermore, the ability of AI to rearrange and reassess various linguistic elements in a plethora of ways also seems similar to the Derridean concept of “différance.” Thus, not only does the absence of a ‘significant authorial voice’ in AI-developed text seem to have an uncanny similarity with textual hegemonies, but they also “force the reader to confront ambiguity and to consider multiple meanings in a text”. Additionally, the futility that exists in an attempt to derive an overarching ideological assumption through a text seems to be included by the production of texts through AI, as

there are multiple ways in which a text is able to be read (Bushell and Hutcheon, 2025).

8.12 Future Directions

The way forward for AI in literature is hybrid creativity, as human-AI co-creations are poised to usher in new literary genres, interactive narratives, and unique storytelling experiences for readers. New advancements in multilingual AI analysis may also open up access to world literature comparatively.

But, at the same time, these developments need to be regulated by some ethical standards that care about and provide for intellectual works, representation, and rights. Literature would remain an important tool in exploring the ramifications of intelligent technologies in culture in the future.

8.13 Conclusion

AI is an exemplary transformative force in the context of contemporary literary discourse. Not only does AI constitute a significant force in the production of literary material, but its implications can be seen in how we critically analyse the same material. Instead of marking the end of human creativity in literature, AI calls for the redefinition of the very concept of authorship in literary discourse.

References

- [1] Begus, N. (2024). Engaging Comparative Literature in AI Development. <https://doi.org/10.31219/osf.io/z9pxn>
- [2] Boden, M. A. (2004). *The creative mind: Myths and mechanisms*. Routledge. <https://api.taylorfrancis.com/content/books/mono/download?identifierName=doi&identifierValue=10.4324/9780203508527&type=googlepdf>
- [3] Boden, M. A. (2016). *AI: Its nature and future*. Oxford University Press, Great Britain, [https://books.google.com/books?hl=en&lr=&id=yDQTDA AAQBAJ&oi=fnd&pg=PP1&dq=Boden+M+A+\(2016\)+AI:+Its+nature+and+future.+Oxford+University+Press,+Great+Britain.&ots=T2kq3A61M6&sig=OxFH4u7uusF5JeQImMqna_7P46g](https://books.google.com/books?hl=en&lr=&id=yDQTDA AAQBAJ&oi=fnd&pg=PP1&dq=Boden+M+A+(2016)+AI:+Its+nature+and+future.+Oxford+University+Press,+Great+Britain.&ots=T2kq3A61M6&sig=OxFH4u7uusF5JeQImMqna_7P46g)
- [4] Bushell, S., and Hutcheon, R. L. (2025). *New approaches for digital literary mapping: Chronotopic cartography*. Cambridge University Press. <https://www.cambridge.org>
- [5] Chan, C. K. Y., and Colloton, T. (2024). *Generative AI in higher education: The ChatGPT effect*. Routledge. <https://www.taylorfrancis.com/books/>

- oamono/10.4324/9781003459026/generative-ai-higher-education-cecilia-ka-yuk-chan-tom-colloton
- [6] Fitkov-Norris, E., and Kocheva, N. (2023). Fitkov-Norris, E., Kocheva, N., and Bhimireddy, N. (2023, June). Are we there yet? Thematic analysis, NLP and Machine Learning for academic research: a comparative review. In *FBSS Research Conference 2023*. <https://researchinnovation.kingston.ac.uk/en/publications/are-we-there-yet-thematic-analysis-nlp-and-machine-learning-for-a-2/>
 - [7] Floridi, L. (2019) *The logic of information: A theory of philosophy as conceptual design*. Oxford University Press. <https://doi.org/10.1093/os/o/9780198833635.001.0001>
 - [8] Haigh, T. (2007). Remembering the office of the future: The origins of word processing and office automation. *IEEE Annals of the History of Computing*, 28(4), 6-31. <https://doi.org/10.1109/MAHC.2006.20>
 - [9] Hayles, N. K. (2002). *Writing machines*. MIT Press, Massachusetts. https://monoskop.org/images/b/bf/Hayles_N_Katherine_Writing_Machines.pdf
 - [10] Hayles, N. K. (2005). *My mother was a computer: Digital subjects and literary texts*. University of Chicago Press. <https://doi.org/10.7208/chicago/9780226321493.001.0001>
 - [11] Hayles, N. K. (2012). *How we think: Digital media and contemporary technogenesis*. University of Chicago Press <https://dms484.wordpress.com/wp-content/uploads/2017/01/hayles-how-we-think.pdf>
 - [12] Herbert, G. E. (2015). Morphing technologies, changing literacies: The reshaping of narrative in a digital world. *Storyworlds: A Journal of Narrative Studies*, 7(1), 1-20. <https://doi.org/10.5250/storyworlds.7.1.0001>
 - [13] Jain, P. (2025). AI in English classrooms: Threat or opportunity for teachers? *IJRSML*. https://www.raijmr.com/ijrsml/wp-content/uploads/2026/01/IJRSML_2025_vol13_Sp.-issue_04_paper_08.pdf
 - [14] Jenkins, A. R. (2018). *From pen to print: Virginia Woolf, materiality and the art of writing* (Doctoral dissertation, Cardiff University). <https://orca.cardiff.ac.uk/id/eprint/113424/12/113424%20DEC%20PAGE%20REMOVED.pdf>
 - [15] Jockers, M. L. (2013). *Macroanalysis: Digital methods and literary history*. University of Illinois Press. <https://www.press.uillinois.edu>
 - [16] Kirschenbaum, M. G. (2008). New media and the forensic imagination. *Mechanisms*. <https://raley.english.ucsb.edu/wp-content/Engl800/Kirschenbaum-intro.pdf>
 - [17] Lanigan, S. (2025). AI and pedagogy: Where machines help and where they must not replace human judgement.

- [18] Manovich, L. (2001) *The language of new media*. MIT Press. <https://cjc.utppublishing.com/doi/full/10.22230/cjc.2002v27n1a1280>
- [19] McLuhan, M. (1964) *Understanding media: The extensions of man*. McGraw-Hill. <https://designopendata.wordpress.com/wp-content/uploads/2014/05/understanding-media-mcluhan.pdf>
- [20] Moretti, F. (2013) *Distant reading*. Verso. <https://www.versobooks.com>
- [21] Ong, W. J. (1982) Orality and literacy: The technologizing of the word. Routledge. <https://api.taylorfrancis.com/content/books/mono/download?identifierName=doi&identifierValue=10.4324/9780203103258&type=googlepdf>
- [22] Poibeau, T. (2025) *Understanding Conversational AI: Philosophy, Ethics, and Social Impact of Large Language Models*. London: Ubiquity Press. <https://doi.org/10.5334/bde>.
- [23] Raj, S., and Bansal, R. (2024) Impact of the printing press: Revolutionizing communication in the Renaissance. *International Journal for Innovative Engineering and Management Research*, 13, 382-387. <https://ijiemr.org/public/uploads/paper/443661713794441.pdf>
- [24] Tenen, D. (2017). *Plain text: The poetics of computation*. Stanford University Press. <https://www.sup.org>
- [25] Underwood, T. (2019) *Distant Horizons: Digital Evidence and Literary Change*. University of Chicago Press, Chicago Scholarship Online, 2019. <https://doi.org/10.7208/chicago/9780226612973.001.0001>
- [26] Woodward, D. (1980). The printing press as an agent of change. *Imago Mundi*, 32(1), 95-97. <https://doi.org/10.1017/CBO9780511817913>

Chapter 9

ROLE OF ARTIFICIAL INTELLIGENCE IN CLIMATE CHANGE PATTERNS: OPPORTUNITIES, CHALLENGES AND ENVIRONMENTAL SUSTAINABILITY

Kulwinder Kaur

Assistant Professor, Department of Geography, Khalsa College for Women, Civil Lines, Ludhiana, Punjab, India- 141001.

Email: kaivi415@gmail.com

Abstract

Climate change impacts play a crucial role in understanding the complexities of global challenges. This chapter will highlight the potential of artificial intelligence (AI) along with its applications to addressing the climate change challenges such as sea level rise, deforestation monitoring, urban heat mapping, extreme weather forecasting events, biodiversity conservation and renewable energy resources management. Climate change is a big threat to today's human life that impacts everyone; people are working to mitigate its impacts with technological and scientific solutions. AI will greatly impact analysis of data, weather predictions and the management of industrial pollution and energy resources. AI-based sustainable farming will be beneficial for environmental sustainability, as it will predict weather changes, forest fires, which ultimately help to improve environmental reforestation. AI by accelerating energy research and alignment with global initiatives for a sustainable future will efficiently enhance the optimum climate patterns. AI, as an effective and affordable system-based tool, is able to address the challenges of climate change mitigation plans (Haider et al., 2025).

Keywords: Climate Change, Artificial Intelligence, Deforestation Monitoring, Environmental Reforestation, Sustainable Future

9.1 Introduction

Climate change is a phenomenon that can be explained by enduring alterations in the weather patterns and has the capacity for detrimental impacts on the environment and human well-being; it also decreases the sustainability of lives in numerous sectors. Impacts of climate change are often interconnected, diverse and complex, from global temperature rise to extreme events like ecosystem disruption. Unpredictable changes in weather phenomena threaten agriculture and food availability and alterations in biological processes are responsible for extinction of numerous species, resulting in biodiversity loss. Conventional methods used to analyse and visualize data had some limitations, but recent advancements like AI offer new opportunities to handle complexities in datasets and also provide innovative solutions to visualize climate change impacts, AI techniques specifically Machine Learning enables us to extract meaningful data insights from large heterogeneous datasets and is also helpful for the researcher to know the hidden relationships that may not be available through manual analyses.

AI is a technique that can be defined as a set of capabilities to perform different tasks that require human intelligence. It is an extremely broad field that not only covers the breakthroughs of the past few years but also includes the achievements of the first electronic computers of the 1940s. AI is concerned about learning, reasoning and perception. AI and machine learning enable organization's adaptive decision-making and mimic human intelligence (Halid et al., 2024). AI is a field of computer technology that is able to finish the task usually performed by humans. The rapid expansion of AI raised a life-changing wave and global concerns and highlighted challenges associated with climate change that led us towards the adoption of renewable and clean energy resources, which ultimately includes decision-making and predictive modelling considering environmental and lifecycle sustainability (Ramya and Singh, 2024). In India, projects like FLUXNET and INDOFLUX (collaborative project department of science and technology, ISRO and Indo-US Science and Technology Forum, US) are being used to monitor climatic change and the effects of global warming in the Indian subcontinent and also focus on estimated climatic and temperature changes in the external environment (Sundareshwar et al., 2007). Green cloud computing enables easy access to data from

anywhere in the world, making it available to a large number of users (Deshmukh et al., 2025; Paul et al., 2020). Integrating AI technologies enhances our understanding to address the climate crisis, such as extreme weather events, with the analysis of a vast database of climate patterns and predictions. The tourism industry is also facing catastrophic situation due to the adverse impacts of climate change (Kumar et al., 2024). Nowadays, researchers are concerned with the strategies of mitigation and adaptation in various sectors and the majority of them recognize AI as a crucial technology to fight climate change. In a report by PwC, it was reported that AI has the potential to decrease greenhouse gas emissions by 4% and also contribute 5.2 trillion dollars to the global economy by 2030 (Anonymous, 2019).

9.2 Role of AI In Climate Change: Opportunities In Mitigation Strategies

Decarbonization technology is considered a conventional method to tackle climate change that includes reduction in CO₂ emission, alternative fossil fuels and adoption of renewable energy resources (Rudnick et al., 2022). These days, AI offers a vast level of understanding of climate patterns and forecasting that assists in designing more effective mitigation strategies. AI based smarter machines are able to differentiate between biological organisms and pollutants. It can be the fighter for air pollutants, as it has a plethora of datasets to make predictions of air quality and help to check air pollution (Aayush et al., 2020).

AI-produced mitigation model will be based on large amount of information from different sources, including satellites, weather stations and ocean buoys, that enables scientists, researchers and policymakers to understand the current situation and to design more effective mitigation policies (Charles, 2024). AI-based forecasted warnings related to critical events such as hurricanes, floods and droughts will produce accurate and timely predictions that help us to save lives and enable communities to prepare and respond in a better way (Kumar et al., 2024). It will also help to increase the yield, pest control, etc. Resilience and adaptive capacity can be enhanced by making interactive maps and support systems for first responders of extreme events, so that the evacuating at-risk areas can be prepared to respond more effectively. By analyzing climate pattern modifications appropriately, AI can maximize the renewable energy farms like wind

and solar farms, which reduces the use of fossil fuels. By recognizing inefficiencies, AI can help cities by suggesting the optimal use of water and energy resources that enhance resource management. AI boosted the conventional energy saving techniques. With the decrease in GHG emission and the encouragement of renewable energy sources, an AI-based Energy Management System plays a crucial role in climate change mitigation (Miller et al., 2024).

As AI is able to process a huge amount of data, it will help policymakers to understand which policies are best to mitigate climate change. AI-based predictions include wide variety of technologies and methodologies, such as machine learning algorithms, statistical models and deep learning architectures that provide hierarchical representations and patterns, which enable the production of more robust and generalizable predictions (Quadri et al., 2026).

Satellite imagery and remote sensing provide important data related to changes in the environment, such as deforestation, land degradation, coral bleaching, etc. AI-produced satellite images enable researchers to integrate multispectral or hyperspectral and radar data that provide information about the vegetation health, soil moisture and water quality. Radar images are able to penetrate clouds and vegetation, which can give data of surface elevation and terrain features. Intelligent sensors are able to collect data of soil moisture content, soil composition, etc. (Krejcar and Namazi, 2026). Traditional methods of communication struggle to engage the public effectively in climate change mitigation processes. AI-driven data through maps, charts and animations enables users to explore and understand the complex relationships; it allows users visualizations and conversational interfaces instead of scientific papers and text reports, with which it is now easier to involve more people and stakeholders in climate change communication (Neri et al., 2025).

Predictions related to sea level rise generated by AI are based on historic data and also forecast future sea level rise and coastal geomorphology. Visualization of these predictions through different tools and dashboards has a great impact on stakeholders to understand the consequences of sea level rise and flooding. With AI-driven deforestation monitoring systems now, researchers are able to analyze data of satellite imagery and remote sensing data in a much easier way (Bahari et al., 2023). They can detect

changes in land cover, forest cover, effectiveness of conservation and illegal activities. By visualization of all data related to the above-mentioned activities through interactive maps and dashboards, policymakers and conservationists can track the deforestation trends and sustainable land use practices can be improved to mitigate climate change.

AI produced data is available in high-resolution maps that enable researchers to detect heat-vulnerable populations in cities, and mitigation policies such as open green spaces and cooling prioritization for urban heat can be designed in a better way to enhance resilience and sustainability in urban communities. AI technologies make urban and rural areas smarter, with the intelligent robotic support system tracking of air pollution levels becoming easy. By tracking waste dumping sites and detecting illegal dumping, AI is helpful in waste management. AI has the potential to harvest crops at higher volume as well as at faster rate as compared to human laborers and farmers can monitor weeds and spray them easily (Nezhad et al., 2025).

9.3 Environmental Sustainability Through AI

Using AI and machine learning applications, the Department of Energy SLAC, National Accelerator Laboratory, detects fluctuations in the power grid system and restores energy in grid failure. AI applications offer potential solutions to optimize energy use (Chui, 2017). Precision farming is another example where AI-based sensors collect data on soil composition and moisture and AI applications also provide recommendations for the input of resources in the field (Soussi et al., 2024). An AI-based application can manage transportation dynamics, allow drivers to effectively manage their routes, optimize speed on the highway by providing estimated signal timings at intersections that will be helpful for smooth traffic flow, reduce fuel consumption, etc. (Sharma et al., 2021).

9.4 Challenges And Future Directions

New techniques and methodologies are continuously evolving in AI. It is the need of the hour to harness the full potential of AI to address new challenges in climate change. Researcher's efforts are more focused on capabilities and applications based on interdisciplinary collaboration and user-centered innovations to maximize the impact of AI to address climate change challenges. Engaging policymakers,

scientists and community members under one umbrella can foster innovation and data integration to improve the usability of AI-based visualized tools. To develop AI techniques in research the approach must consider environmental impacts of innovations as world need green and environmentally friendly AI (Wu et al., 2022). Interdisciplinary partnerships and collective expertise can create diverse stakeholders to solve complex challenges.

Management of ethical standards of data privacy is essential in AI-driven databases; otherwise, environmental injustice and inequalities may generate disproportionate impact on the communities. To address the ethical concerns, transparency and accountability of AI systems are required. Quality, accessibility and reliability of data are another critical challenge for AI, as climate-related data usually have missing values and outliers. To address this problem, collective efforts of policymakers, data providers, and researchers must be there to improve data sharing and the data collection mechanism. Data privacy protocols must be there (Ghosh, 2025).

AI and machine learning require AI expertise and AI-skilled manpower, for which India is lagging behind at the global level. AI-driven technologies require a high cost of implementation. Lack of awareness is another challenge for AI, particularly in developing countries like India.

9.5 Adverse Impacts of AI on The Environment

AI-equipped software demands an enormous amount of electricity. AI-based software produced a large amount of e-waste. An AI application's functioning consumes a large amount of water. AI-driven applications produce carbon dioxide that may adversely impact marginalized communities. AI-based data can be misused. AI implementation requires a high cost (Wang et al., 2021).

9.6 Conclusion

Modern problems need modern solutions. AI is one of the important and helpful tools to make our planet healthier, as it offers powerful solutions and methodologies to visualize the impact of climate change. It enables scientists and researchers to understand the complexity of the different problems. AI-based applications enhance public awareness and mobilize collective efforts to build a sustainable world

for future generations. But along with this, it is also essential to note that AI applications are rising worldwide but mostly in developed nations, since environmental sustainability is a global concern, so government bodies and institutions are needed to introduce a proper setup of AI-allied technologies in different sectors such as agriculture, forestry and environment, etc.

References

- [1] Aayush, K., Vishal, D., Hammad, N., and Manu, K. S. (2020). Application of artificial intelligence in curbing air pollution: The case of India. *Asian Journal of Management*, 11(3), 285-290. <https://doi.org/10.5959/2321-5763.2020.00044.X>
- [2] Anonymous (2019) Using AI to better manage the environment could reduce greenhouse gas emissions, boost global GDP by up to US \$5 trillion and create up to 38m jobs by 2030. <https://www.pwc.com/gx/en/newsroom/press-releases/2019/ai-realise-gains-environment.html>
- [3] Bahari, N. A. A. B. S., Ahmed, A. N., Chong, K. L., Lai, V., Huang, Y. F., Koo, C. H., Ng, J. L., and El-Shafie, A. (2023). Predicting Sea Level Rise Using Artificial Intelligence: A Review. *Archives of Computational Methods in Engineering*, 30(7), 4045-4062. <https://doi.org/10.1007/s11831-023-09934-9>
- [4] Charles, A. A. Integrating Artificial Intelligence and Machine Learning in Climate Modeling. <https://doi.org/10.13140/RG.2.2.15586.34248/2>
- [5] Chui, G. (2017) SLAC-Led Project Will Use Artificial Intelligence to Prevent or Minimize Electric Grid Failures. <https://www6.slac.stanford.edu/news/2017-09-14-slac-led-project-will-use-artificial-intelligence-prevent-or-minimize-electric-grid>
- [6] Deshmukh, V. D., Singh, S., and Waghmare, S. (2025). Green Cloud Computing: Energy-Efficient Solutions for Sustainable IT Infrastructure. *International Journal of Mobile and Cloud Systems Engineering*. <https://doi.org/10.46610/IJMCSE.2025.v01i02.002>
- [7] Ghosh, M. (2025). Artificial intelligence (AI) and ethical concerns: a review and research agenda. *Cogent Business and Management*, 12(1), 2551809. <https://doi.org/10.1080/23311975.2025.2551809>
- [8] Haider, S. J., Srivastava, V. K., Kumar, B., and Hasan, S. Z. (2025). Artificial Intelligence in Energy Research and Climate Change. *Indian Journal of Artificial Intelligence and Neural Networking (IJAINN)*, 5(5), 4-7. <https://doi.org/10.54105/ijainn.E1104.05050825>
- [9] Halid, H., Ravesangar, K., Mahadzir, S. L., and Halim, S. N. A. (2024). Artificial intelligence (AI) in human resource management (HRM). In *Building the future with human resource management* (pp. 37-70).

- Cham: Springer International Publishing. https://doi.org/10.1007/978-3-031-52811-8_2
- [10] Krejcar, O., and Namazi, H. (2026). AI in remote sensing and satellite image processing-a review. *Environmental Earth Sciences*, 85(3), 78. <https://doi.org/10.1007/s12665-025-12798-w>
 - [11] Kumar, C. S., Vani, D. D., Damodar, K., Manoharan, G., and Veerapaga, N. (2024). Climate change mitigation through AI solutions. In *Gastronomic sustainability solutions for community and tourism resilience* (pp. 37-59). IGI Global Scientific Publishing. <https://doi.org/10.4018/979-8-3693-4135-3.ch003>
 - [12] Miller, T., Durlik, I., Kostecka, E., Łobodzińska, A., and Matuszak, M. (2024). The emerging role of artificial intelligence in enhancing energy efficiency and reducing GHG emissions in transport systems. *Energies*, 17(24), 6271. <https://doi.org/10.3390/en17246271>
 - [13] Neri, G., Marshall, S., Chan, H. K. H., Yaghi, A., Tabor, D., Sinha, R., and Mazumdar, S. (2025). Data visualization in AI-assisted decision-making: a systematic review. *Frontiers in Communication*, 10, 1605655. <https://doi.org/10.3389/fcomm.2025.1605655>
 - [14] Nezhad, M. M., Moradian, S., Guezgouz, M., Shi, X., Avelin, A., and Wallin, F. (2025). A GIS-portal platform from the data perspective to energy hub digitalization solutions-A review and a case study. *Renewable and Sustainable Energy Reviews*, 223, 116019. <https://doi.org/10.1016/j.rser.2025.116019>
 - [15] Paul, P., Bhimali, A., Aithal, P. S., Kalishankar, T., and Saavedra M, R. (2020). Artificial intelligence and cloud computing in environmental systems-towards healthy and sustainable development. *International Journal of Inclusive Development*, 6(1), 01-08. <https://ssrn.com/abstract=3709187>
 - [16] Quadri, S. S. A., Tasadduq, H. A., Tabassum, S., Ahmad, M., and Gishkori, R. (2026). Artificial Intelligence and Climate Governance: The Emerging Politics of Data-Driven Environmental Policy. *Journal Of Psychology, Health And Social Challenges*, 4(01), 39-47. <https://doi.org/10.63075/9z2t0s71>
 - [17] Ramya, R. V., and Singh, R. K. (2024). The role of artificial intelligence in climate change visualisation. *Idealistic Journal of Advanced Research in Progressive Spectrums* (IJARPS) eISSN-2583-6986, 3(04), 48-54. <https://journal.ijarps.org/index.php/IJARPS/article/view/341>
 - [18] Rudnick, I., Duenas-Martinez, P., Botterud, A., Papageorgiou, D. J., Mignone, B. K., Rajagopalan, S., Harper, M. R. and Ganesan, K. (2022). Decarbonization of the Indian electricity sector: Technology choices and policy trade-offs. *Science*, 25(4). <https://doi.org/10.1016/j.isci.2022.104017>

- [19] Sharma, M., Bansal, A., Kashyap, V., Goyal, P., and Sheikh, T. H. (2021). Intelligent traffic light control system based on traffic environment using deep learning. In *IOP conference series: Materials Science and Engineering*, 1022(1), 012122. IOP Publishing. <https://doi.org/10.1088/1757-899X/1022/1/012122>
- [20] Soussi, A., Zero, E., Sacile, R., Trincherio, D., and Fossa, M. (2024). Smart Sensors and Smart Data for Precision Agriculture: A Review. *Sensors*, 24(8), 2647. <https://doi.org/10.3390/s24082647>
- [21] Sundareshwar, P. V., Murtugudde, R., Srinivasan, G., Singh, S., Ramesh, K. J., Ramesh, R., Verma, S. B., Agarwal, D., Baldocchi, D., Baru, C. K., and Baruah, K. K. (2007). Environmental monitoring network for India. *Science*, 316(5822), 204-205. <https://doi.org/10.1126/science.1137417>
- [22] Wang, P., Zhang, L. Y., Tzachor, A., and Chen, W. Q. (2024). E-waste challenges of generative artificial intelligence. *Nature Computational Science*, 4(11), 818-823. <https://doi.org/10.1038/s43588-024-00712-6>
- [23] Wu, C.J., Raghavendra, R., Gupta, U., Acun, B., Ardalani, N., Maeng, K., Chang, G., Aga, F., Huang, J., Bai, C., and Gschwind, M. (2022). Sustainable AI: Environmental implications, challenges and opportunities. *Proceedings of machine learning and systems*, 4, 795-813. <https://doi.org/10.48550/arXiv.2111.00364>

NOTES

This image shows a single sheet of white paper with horizontal ruling lines. The lines are evenly spaced and run across the width of the page. There are no margins, text, or other markings on the paper.

Chapter 10

ROLE OF ARTIFICIAL INTELLIGENCE IN NUTRITION SCIENCES

Manasvi Dua

Dietician, RG Stone Hospital, Ferozepur Road, Ludhiana, Punjab, India-141002.

Email: manasvidua16@gmail.com

Abstract

Artificial intelligence (AI) is transforming nutrition science by enabling tailored nutrition, population-level nutrition surveillance and advanced dietary evaluation. Complex dietary, behavioral and biological data may be studied at a never-before-seen scale thanks to methods like machine learning, deep learning, computer vision and natural language processing. AI has demonstrated promise in enhancing dietary intake assessment accuracy, forecasting individual responses to nutrients and supporting public health initiatives. Misconceptions regarding AI's potential persist despite these advancements. In popular narratives, AI is often emphasized as a replacement for nutrition experts and it is also assumed that AI outcomes are inherently neutral and truthful. Practical constraints of AI systems include incomplete dietary composition databases, low-quality data and algorithmic biases that may worsen health disparities. This chapter highlights the uses of AI in nutrition science, as well as myths and realities, the negative effects of overusing AI in nutrition science and potential future developments.

Keywords: Nutrition, Dietary Assessment, Personalized Nutrition, Ethical Considerations

10.1 Introduction

Rapid transformation has been achieved in the field of healthcare, be it disease diagnosis, prediction, treatment, or health behavior changes, by the implementation of artificial intelligence (AI) (Topol, 2019; Rajpurkar et al., 2022). The use of AI technologies in nutrition science to evaluate and solve methodological issues such as poor dietary evaluation, insufficient personalization of dietary recommendations and ineffective handling of massive amounts of nutrition data is increasing tremendously (Martin et al., 2014; Weber et al., 2014). The conventional methods in the clinical and public health nutrition treatments lost their effectiveness owing to these problems.

According to Goodfellow et al., (2016), AI denotes computational systems with the ability to work on tasks that require human-like intelligence, for instance, computer vision, machine learning, deep learning and natural language processing. The capacity of AI to work on complex, high-dimensional data has resulted in new opportunities for the identification of dietary patterns, real-time monitoring and customized nutrition plans in the field of nutrition research (Zeevi et al., 2015). Though, limitations and drawbacks of AI are often ignored and its potential is exaggerated to the extent that its reach gets distorted (Floridi et al., 2018). This chapter critically reviews the role of AI in nutrition research by differentiating widespread myths from evidence-based truths. It also examines the theoretical basis of AI, implementation in nutritional assessments, practical and ethical constrictions and possible future developments. The chapter highlights the reality of AI rather than its hype and puts forward the inference that AI boosts rather than substitutes human nutrition knowledge when employed within appropriate scientific and ethical frameworks (Topol, 2019; Krittanawong et al., 2022).

10.2 Conceptual Foundations of AI In Nutrition

In general terms, AI is a computational method based on learning from data and then progressive enhancement (Goodfellow et al., 2016). Basically, machine learning algorithms identify patterns and produce probable results based on the data observed (Jordan and Mitchell, 2015), whereas in deep learning (a subset of machine learning), a layered neural network is employed to examine multifaceted

inputs such as images and time-based data (LeCun et al., 2015). With the help of another AI program, i.e., Natural Language Processing uses textual data, for instance, product labels, medical records and dietary recalls, to conveniently extract organized information. Similarly, computer vision helps machines to work on visual inputs, an important ability for picture-based dietary valuation (Boushey et al., 2017). According to studies by Weber et al., (2014) and Sultan et al., (2026), it becomes feasible to perform pattern identification and detection and integration of large datasets in nutrition science and highly progressive dietary analytics by use of such AI tools. Standard conventional statistical approaches are incapable of performing such advanced tasks. Nevertheless, there are certain limits and biases that originate during methodological design and training data, which are reflected in AI models but are not intrinsically objective (Obermeyer et al., 2019).

10.3 Application of AI In Nutrition Science

10.3.1 Automation in Dietary Assessment

Accuracy in dietary assessment is a crucial part of nutrition science and research. The standard manual and conventional methods like 24-hour recalls and food frequency surveys are full of errors due to recall bias, measurements, and social pressure (Thompson and Subar, 2017; Shim et al., 2014). Nutritional assessment systems that are AI-based solve such challenges just by application of computer vision and machine learning to identify food type and approximation of portion sizes from digital photographs (Boushey et al., 2017; Chotwanvirat et al., 2023). These techniques are in fact time-saving and provide more frequent, real-time nutritional information, thereby reducing participants' burden (Martin et al., 2014). But the question "How accurate the data is?" is still a problem. Because of complexity in mixed meals, diverse food cuisines, and variations in illumination, classification performance by AI is usually lowered (Chotwanvirat et al., 2023). Human supervision is still important, and hybrid systems integrating visual data with user prompts and sensor data perform with increased reliability.

10.3.2 Personalized and Precision Nutrition

Personalized and precise nutrition management works on the customization of dietary guidance to every individual based on factors like metabolism, lifestyle behavior, microbiome composition, and most importantly, genetics (Ordovas et al., 2018; Zeevi et al., 2015). AI-based functions work very well in such domains; they combine dissimilar datasets and determine customized dietary response patterns. In contrast to conventional dietary recommendations, AI-based predictive models increase accuracy in predicting glycemic responses (Zeevi et al., 2015). Even such advanced systems have drawbacks such as ethical constraints, data privacy breaches, and algorithmic transparency that further hinder therapeutic applications (Price and Cohen, 2019; Rajkomar et al., 2018).

10.3.3 Clinical and Public Health Nutrition

Using clinical decision support systems that examine patient data for detection of malnutrition risk, tracking of dietary adherence, and formation of customized care plans, AI helps nutritionists and medical professionals (Topol, 2019; Krittanawong et al., 2022). AI assistance is feasible by analysis of big data analytics leading to large-scale supervision of food patterns and identification of people at risk (Beam and Kohane, 2018). For example, AI may scan social media or retail purchase data to detect developing dietary patterns, which supports policy planning (Susanto et al., 2023).

10.4 Myths and Reality Regarding AI In Nutrition

The use of AI is sometimes exaggerated to an extent where its reliability is ignored. There are certain myths related to AI and nutrition science that are compared with facts that may justify the existential importance of human knowledge.

10.4.1 Myth: AI can replace nutrition professionals

The idea that AI can replace human care and expertise is a well-known and prominent issue on the internet, yet it is untrue. In terms of the application of AI-backed technologies in nutritional science, it is a fact that AI is elevating the levels of analysis by highly qualified dietitians, but that it can replace the professionals is a pure myth. AI holds no empathy, judgement or cultural awareness, which a medical

professional earns from years of practice and experience (Floridi et al., 2018; Topol, 2019). Hybrid strategies employing AI techniques and human knowledge can enhance research and developments rather than replace professional skills (Beam and Kohane, 2018).

10.4.2 Myth: AI results are objective and accurate by nature

The impression that AI-generated information is accurate and precise and also that the outputs received are impartial is another common misconception. Any misinformation or error resulting from an inefficiently trained AI model reduces the output quality, and the information is compromised by bias and mistakes (Obermeyer et al., 2019). Thus, it becomes necessary that AI-generated information must be cautiously interpreted by nutrition expertise (Thompson and Subar, 2017).

10.4.3 Myth: All human bias is eliminated by AI

Human errors and biases are very common, but can these be eliminated using AI? That is still a question. It's a huge myth that machines cannot make mistakes; AI models are based on training on non-representative datasets, so they might magnify preexisting biases (Obermeyer et al., 2019). Therefore, nutrition-related recommendations based on biased AI models may unintentionally cause harm rather than benefit (Rajkomar et al., 2018).

10.5 Advantages and Disadvantages of AI In Nutrition Sciences

The AI models are very useful owing to their advantages but there are certain limitations where these models fail to deliver valuable outputs. Table 10.1 highlights the advantages and disadvantages of AI in nutrition sciences.

10.6 Restrictions of AI In Nutrition

AI faces restrictions when employed in medical fields without acknowledging variations in the genetical information of the population, eating habits, food diversity, an individual's metabolism, and many other factors. Other issues, for example, complex, mixed meals and visual ambiguity are common challenges for food picture identification (Chotwanvirat et al., 2023). Inadequate food composition

Table 10.1: advantages and disadvantages of AI in nutrition sciences

Advantages	Disadvantages
Higher accuracy of AI-assisted nutrition-based information if correct input is provided to the system (Detopoulou et al., 2023).	Human care is important and crucial in nutrition, which is missed out by AI software, this is undoubtedly a significant drawback. Using AI instead of a nutritionist would make it difficult for patients to connect and feel included during consultations (Detopoulou et al., 2023).
Quick accessibility of data. Artificial intelligence cuts down on the amount of time a person must spend searching through numerous websites in order to find the answers. AI generates brief responses based on the user’s data input. (Chatelan et al., 2023)	Bias and misinformation in the development of AI-based tools and systems might result from data gaps, out-of-date information and social injustices caused by a lack of statistics and data (Arslan, 2024). This is undoubtedly a significant drawback.
Inexpensive AI search engines are easily available that provide real time results. When compared to dietician assistance, some people prefer the cost-effectiveness and great accessibility of free AI technologies for nutritional guidance and dietary assessments (Chatelan et al., 2023).	Users may obtain advice that is harmful to their health after they have access to biased, out-of-date, or false information (Bond et al., 2023).

databases reduce the accuracy of nutrient approximation (Thompson and Subar, 2017). Furthermore, AI models typically execute well in controlled research settings but exhibit reduced accuracy in

real-world circumstances due to overfitting and lack of external validation (Beam and Kohane, 2018; Weber et al., 2014). Regulatory frameworks for AI in healthcare are still underway, producing doubt about requirements for safety, objectivity and therapeutic effectiveness. The use of AI in nutrition is still unequal in the absence of clear regulatory monitoring (Topol, 2019; Susanto et al., 2023).

10.7 Prospective Paths

Future advancements in AI for nutrition will concentrate on improving explainability, equity and communication with real-world healthcare systems. Explainable AI can increase transparency by allowing patients and clinicians to comprehend recommendations made by AI (Floridi et al., 2018; Rajkomar et al., 2018). By combining AI with wearable and sensor technology, richer, continuous nutrition and health data could be acquired, enabling dynamic customization (Zeevi et al., 2015). Equity-focused AI research that considers a range of dietary patterns and global populations is essential to prevent widening health inequities (Obermeyer et al., 2019). Interdisciplinary collaboration between nutrition scientists, data scientists, ethicists and legislators will be crucial for ethical adoption and responsible innovation (Char et al., 2018; Price and Cohen 2019).

10.8 Conclusion

This chapter covers the employment of AI in nutrition science and it can be concluded that it offers substantial predictions to better nutrition science and practice, including enhanced nutritional assessment, personalized nutrition and population health analytics. Yet, myths surrounding its efficiency and limitations must be addressed carefully. It must be considered a powerful tool that augments human expertise rather than a replacement for nutrition specialists.

References

- [1] Arslan, S. (2024). Decoding dietary myths: the role of ChatGPT in modern nutrition. *Clinical Nutrition ESPEN*, 60, 285-288. <https://doi.org/10.1016/j.clnesp.2024.02.022>
- [2] Beam, A. L., and Kohane, I. S. (2018). Big data and machine learning in health care. *JAMA*, 319(13), 1317-1318. <https://doi.org/10.1001/jama.2017.18391>

- [3] Bond, A., Mccay, K., and Lal, S. (2023). Artificial intelligence and clinical nutrition: What the future might have in store. *Clinical nutrition ESPEN*, 57, 542-549. <https://doi.org/10.1016/j.clnesp.2023.07.082>
- [4] Boushey, C. J., Spoden, M., Zhu, F. M., Delp, E. J., and Kerr, D. A. (2017). New mobile methods for dietary assessment: review of image-assisted and image-based dietary assessment methods. *Proceedings of the Nutrition Society*, 76(3), 283-294. <https://doi.org/10.1017/S0029665116002913>
- [5] Char, D. S., Shah, N. H., and Magnus, D. (2018). Implementing machine learning in health care—addressing ethical challenges. *The New England Journal of Medicine*, 378(11), 981. <https://doi.org/10.1056/NEJMp1714229>
- [6] Chatelan, A., Clerc, A., and Fonta, P. A. (2023). ChatGPT and future artificial intelligence chatbots: what may be the influence on credentialed nutrition and dietetics practitioners? *Journal of the Academy of Nutrition and Dietetics*, 123(11), 1525-1531. <https://doi.org/10.1016/j.jand.2023.08.001>
- [7] Detopoulou, P., Voulgaridou, G., Moschos, P., Levidi, D., Anastasiou, T., Dedes, V., Diplari, E.M., Fourfour, N., Giaginis, C., Panoutsopoulos, G. I., and Papadopoulou, S. K. (2023). Artificial intelligence, nutrition, and ethical issues: A mini-review. *Clinical Nutrition Open Science*, 50, 46-56. <https://doi.org/10.1016/j.nutos.2023.07.001>
- [8] Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., Rossi, F., and Schafer, B. (2018). AI4People—An ethical framework for a good AI society. *Minds and Machines*, 28, 689–707. <https://doi.org/10.1007/s11023-018-9482-5>
- [9] Goodfellow, I., Bengio, Y., and Courville, A. (2016). Deep feedforward networks. *Deep Learning*, 1, 161-217. <https://www.deeplearningbook.org>
- [10] Jordan, M. I., and Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, 349(6245), 255-260. <https://doi.org/10.1126/science.aaa8415>
- [11] Sultan, S., Saad Montasser, H., and AbdElgaberAbdElmawgod, S. (2026). AI-Driven nutrition: A review of deep learning applications, challenges, and future directions. *Journal of Artificial Intelligence in Engineering Practice*, 3(1), 1-30. <https://doi.org/10.21608/jaiep.2026.459253.1052>
- [12] LeCun, Y., Bengio, Y., and Hinton, G. (2015). Deep learning. *Nature*, 521, 436-444. <https://doi.org/10.1038/nature14539>
- [13] Martin, C. K., Nicklas, T., Gunturk, B., Correa, J. B., Allen, H. R., and Champagne, C. (2014). Measuring food intake with digital photography. *Journal of Human Nutrition and Dietetics*, 27, 72-81. <https://doi.org/10.1111/jhn.12014>

- [14] Obermeyer, Z., Powers, B., Vogeli, C., and Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science*, 366, 447-453. <https://doi.org/10.1126/science.aax2342>
- [15] Ordovas, J. M., Ferguson, L. R., Tai, E. S., and Mathers, J. C. (2018). Personalised nutrition and health. *British Medical Journal*, 361. <https://doi.org/10.1136/bmj.k2173>
- [16] Chotwanvirat, P., Prachansuwan, A., Sridonpai, P., and Kriengsinyos, W. (2024). Advancements in using AI for dietary assessment based on food images: scoping review. *Journal of Medical Internet Research*, 26, e51432. <https://doi.org/10.2196/51432>
- [17] Price, W. N., and Cohen, I. G. (2019). Privacy in the age of medical big data. *Nature medicine*, 25(1), 37-43. <https://doi.org/10.1038/s41591-018-0272-7>
- [18] Rajkomar, A., Oren, E., Chen, K., Dai, A. M., Hajaj, N., Hardt, M., Liu, P. J., Liu, X., Marcus, J., Sun, M., and Sundberg, P. (2018). Scalable deep learning for electronic health records. *npj Digital Medicine*, 1, 18. <https://doi.org/10.1038/s41746-018-0029-1>
- [19] Rajpurkar, P., Chen, E., Banerjee, O., and Topol, E. J. (2022). AI in health and medicine. *Nature medicine*, 28(1), 31-38. <https://doi.org/10.1038/s41591-021-01614-0>
- [20] Shim, J. S., Oh, K., and Kim, H. C. (2014). Dietary assessment methods in epidemiologic studies. *Epidemiology and Health*, 36, e2014009. <https://doi.org/10.4178/epih/e2014009>
- [21] Thompson, F. E., and Subar, A. F. (2017). Dietary assessment methodology. *Nutrition in the Prevention and Treatment of Disease*, 5-48. <https://doi.org/10.1016/B978-0-12-802928-2.00001-1>
- [22] Topol, E. J. (2019). High-performance medicine: the convergence of human and artificial intelligence. *Nature Medicine*, 25(1), 44-56. <https://doi.org/10.1038/s41591-018-0300-7>
- [23] Weber, G. M., Mandl, K. D., and Kohane, I. S. (2014). Finding missing connections in biological data. *The Journal of American Medical Association*, 311(24), 2479-80. <https://doi.org/10.1001/jama.2014.4228>
- [24] Zeevi, D., Korem, T., Zmora, N., Israeli, D., Rothschild, D., Weinberger, A., Ben-Yacov, O., Lador, D., Avnit-Sagi, T., Lotan-Pompan, M., and Suez, J. (2015). Personalized nutrition by prediction of glycemic responses. *Cell*, 163(5), 1079-1094. <https://doi.org/10.1016/j.cell.2015.11.001>

NOTES

This image shows a single sheet of white paper with horizontal ruling lines. The lines are evenly spaced and run across the width of the page. There are no margins, text, or other markings on the paper.

Chapter 11

FROM CONCEPT TO CONCLUSION: THE ROLE OF ARTIFICIAL INTELLIGENCE TOOLS IN RESEARCH

Parminder Kaur* and Harpreet Kaur

Assistant Professor, Guru Tegh Bahadur National College, Dakha, India-141101.

Email*: neetugugnani@gmail.com

Abstract

Artificial Intelligence (AI) has emerged as a transformative tool in the area of academic research, especially in field of social sciences. From identifying a research problem to literature review, data collection, data analysis, report writing and selecting an appropriate journal, AI-powered tools are restyling the whole research procedure. This study provides a comprehensive review of some specific AI tools such as Scite, Elicit, Research Rabbit, Julius AI, Zotero, Mendeley etc., that enhances the efficiency and accuracy of the research process. The study will show how these tools are transforming the field of social sciences by integrating AI tools across different stages of research process. The main objective of this paper is to foster an informed approach to integrate AI tools in the research arena, ensuring that researchers are knowledgeable to use these tools to boost the quality and output of their research work. In the end, the study concludes that although AI-powered tools enhance efficacy of the research productivity, but critical human thinking remains crucial for ethical and meaningful research procedures.

Keywords: Academic Research, AI-powered Tools, Ethical Research, Research Process, Social Science

11.1 Introduction

Artificial intelligence tools are software programmes that assist human intellect in decision making by using various forms of artificial intelligence to perform certain responsibilities. These tools offer variety of features such as picture recognition, voice recognition, machine learning, data analysis etc. so that academicians can emphasize more on critical thinking and interpretation of results (Venkatesh, 2022). In the beginning, the term 'AI' has been used by J McCarthy in the year 1955 while preparing a research proposal for a conference. There is no universal accepted explanation of AI, but it has been lightly inferred as the combination of human intelligence and machines (Ali et al., 2020). AI has been getting high amount of attention in various field such as healthcare, social sciences, research as well as academia in recent years. In the arena of research, its significance can be stemmed from its ability to analyse vast amount of data, to identify tough patterns, to generate useful insights and to systematise the complex problems. For instance, Generative Pre-Trained Transformers (GPTs) are types of deep learning models that are extremely used by researchers in the academic community for numerous reasons such as to produce, analyse, interpret and to summarise critical information (Christou, 2023).

11.2 Emergence of AI In Academic Research

The term academic research basically signifies research that is being carried out in higher educational institutes and universities by scholars or intellectuals as a part of their academic training or by teaching faculties as a part of their academic research work. The results of these research work are published either in form of dissertation/Ph.D. thesis or in the form of research papers (Bhatnagar and Bhatnagar, 2024). These tasks generally consist of to define a research problem, to conduct literature review, formulation of research hypothesis/questions, setting up of research objectives, collection of data, using appropriate statistical tools for analysis, interpreting the results, concluding the research work and finally publishing/presenting the research work (Kothari, 2004). As these tasks demand plenty of time and efforts; hence researchers can use AI tools in the area of academic research for conducting literature review, content writing, grammar checking, plagiarism testing, presentation preparation and for many more such things. While

using these AI tools, a researcher can utilise their time to full potential as well as can focus on relevant tasks to efficiently complete their research work.

Although artificial intelligence has existed as a scientific discipline since 1956, but recent developments in the area of generative AI have completely transformed the research landscape (Castillo-Martínez et al., 2024). With the emergence of ChatGPT in 2022, generative AI has positioned as a valuable tool in research problem identification, literature exploration, hypothesis development, reference management and research paper writing. In spite of its growing adoption, none of the existing studies in the literature completely recognised its potential to enhance research competence or to support adaptive learning environment across academic disciplines.

The present study explores the process of research with the help of different AI tools. Numerous AI tools have been explored across the different phases of research to outline emerging research trajectories. The structure of this paper is as follows: Initially, the study outlines the introduction and emergence of AI in academic research to establish a base for understanding the use of AI application under phases of research. Afterwards, the study explains several AI tools used under various stages of the research process and their in-depth usage across all the segments of research journey. In the last section, the paper shows the limitations and ethical concerns of using AI in scientific research in higher education settings. This approach not only contextualizes the study within the broader academic dialogue, but also highlights its potential to inform future research.

11.3 AI Powered Tools for Research Writing

In today's scenario, AI tools play a crucial role in research paper writing. These tools provide assistance to scholar's in different stages of research process. Research paper writing starts with identifying a clear, relevant and researchable research problem which lays foundation of every successful research study. AI-powered tools have emerged as a valuable aid in research problem identification by providing vast amount of literature to scholars, detecting latest trends, and detecting research gaps with high precision (Floris and Renandya, 2025). Tools such as connected papers, elicit aids researchers by identifying patterns in publications, citations, keyword search and

research questions. As a result, scholars can identify a well-defined novel research problem which ultimately enhances the relevance and policy significance of research topics in all the areas of research. Some of the tools are categorised below on the basis of their primary function in research (Table 11.1).

Table 11.1: AI tools used under various stages of the research process

Sr. No.	Research Stage	AI Tools	Core Purpose
1.	Problem Identification	Elicit, Research Rabbit	To identify research gaps and trends
2.	Literature Review	Scite, Connected Papers	Smart citations and mapping
3.	Data Collection	AI survey tools, Web scrappers	Automated data gathering
4.	Data Analysis	Julius AI, JASP	Statistical and Machine learning based analysis
5.	Writing and Editing	Trinka AI, Grammerly	Language and structural improvement
6.	Journal Selection	Elsevier Journal Recommender	Matching manuscripts to journals

The research process comprises of series of steps necessary to carry on the research and following are the different phases of research journey along with different AI tools which assist in that particular phase of research.

11.3.1 Phase I: Concept and Literature Discovery

The research journey begins with selecting a problem which seems to be the most daunting task of research journey. The best way to start is with a past research topic rather than starting a completely novel idea of your own as it will provide a strong foundation to start the research journey. Next step is to conduct a literature review which involves searching and reviewing the published material in order

to gain familiarity about the already decided topic (Jackson, 2009). Selection of a research problem and a thorough literature review take time; however, with the help of AI tools this task can be simplified.

11.3.2 AI-Powered Problem Selection

AI-powered tools such as ChatGPT-4o or Claude 3.5 Sonnet can facilitate essential research activities such as brainstorming concepts, outlining ideas, and generating drafts. These tools can suggest novel and feasible research ideas, advise diverse dimensions of research in any domain. Tools like ChatGPT can offer significant insights during the whole writing process by brainstorming different ideas, generation of content, to overcome writer's block by providing interactive feedback and suggestions so that researchers can focus more on refining and intensifying their concepts, rather than struggling with how to initiate the research journey (Floris and Renandya, 2025).

11.3.3 Assisting in Literature Review with Smart Citations and Article Discovery

The most thought-provoking task of research paper writing is to conduct the literature review as it involves searching, evaluating and synthesizing appropriate academic sources. Here, the researcher has to carry out broad literature survey comprising of studying different academic journals, conference proceedings, government reports, earlier studies etc. (Kothari, 2004). AI driven tools will be a great help to the researcher at this stage. Tools such as Elicit, Scite, Research Rabbit, Connected Papers or Semantic scholar have completely revolutionised this process by making it more rapid and comprehensive. Elicit.ai uses language models to automate the literature review. It can provide related articles even without a perfect keyword match and can also summarise the papers. Hence, it has been widely used by researchers to speed up their research process (Khalifa and Albadowy, 2024). Apart from this, another AI-powered tool Scite.ai uses smart citations and allows scholars to check, if an article's findings have been supported, differentiated or just stated in consequent studies. This is highly useful for academicians to get contested opinions if they are in the process of building or testing a particular theory (Pinzolit, 2023). In addition, Research Rabbit is a free platform for scholars offering them

tailored recommendations, team work opportunities, interactive visualizations and it also incorporates with citation management tools. It allows researchers to create collection of their work, recommends similar papers and visualise the relationship among authors and work in a 'map' layout (Pinzolit, 2023). One more tool Connected Papers creates a visual presentation of an area after entering a 'seed paper' and forms visual clusters based on citation match. It is assisting scholars to recognize a seminal work and the evolving branches of that particular topic.

11.3.4 Phase II: Data Collection and Processing

In the area of social sciences, there are number of ways of collecting the appropriate data and generally the data are available in unstructured formats such as audio recordings, social media posts, PDF documents or interview transcripts. Processing of such documents with traditional methods can be time-consuming. To address this issue, various AI tools are useful. For example, tools like ChatPDF, Humata are highly useful to extract specific variables or data points from lengthy documents and transform them into structured table formats. Besides this, various web scrapping tools such as browse.ai and ParseHub give choice of no-code extraction and help researchers to collect data from various social media platforms, websites or news portals by detecting the required elements and also manage the technical complications. Moving forward, Virtual AI assistants support data cleaning and processing by standardising disorganized scripts, categorising the open-ended survey responses through sentiment as well as thematic analysis, and transcribing audio interviews via speech-to-text models such as Whisper. Together, these AI tools boost data accuracy with minimal manual effort improves the overall proficiency of the research process.

11.3.5 Phase III: Advanced Data Analysis

After collecting the data, the next important phase is the analysis of data. The analysis of data involves number of carefully monitored tasks such as establishing different categories, classifying these categories to raw data by coding, tabulation and then drawing statistical inferences (Jackson, 2009). The computational strength of AI tools can easily detect outliers, handle missing values, and can normalise larger datasets at a faster speed than manual entry thereby

reducing human error and enhancing the reliability of results. To perform advanced statistical analysis, chatbots like Julius AI and JASP are highly useful. Julius AI enables researchers to upload a dataset in CSV or excel format and perform various statistical tools like descriptive analysis, correlation analysis, multiple regression analysis etc. Another important tool JASP is a very good alternative to SPSS since it offers a user-friendly drag and drop interface which allows scholars to perform both frequentist (hypothesis testing, ANOVA, regression, and confidence interval estimation) as well as Bayesian statistics (estimation of posterior probabilities, Bayes factors, and model comparison, offering deeper insights beyond traditional methods) without any hardships. Both these tools perform complex quantitative analysis with limited programming and at the same time maintains the transparency and reproducibility of the research findings.

11.3.6 Phase IV: Writing, Referencing and Editing

The academic writing and research space is more and more supported by wide range of AI tools such as Zotero, Mendeley and EndNote for literature management, organising research materials, and generating citations with word processors (Khalifa and Albadawy, 2024). The much widely used Mendeley application uses AI-driven algorithms to suggest novel research articles based on documents saved in a user's library, thus enabling endless literature search. Another reference management tool Zotero detects citation-based connections among stored PDFs and supports deeper analytical insights. EndNote is mainly useful for large-scale systematic reviews by utilising its AI-assisted features to automate the recovery of full-text PDFs and also manage broad reference databases.

Apart from reference management, AI tools also augment scientific writing and clarity. Various platforms such as Trinka.ai, Hemingway Editor, Grammarly etc. are specially designed for academic and technical writing, suggest grammar corrections in addition to style improvements. These platforms also aid researchers in improving readability by highlighting complex sentences (Alordiah, 2023). Grammarly software is specially designed for real-time grammar checks, tone suggestions, and plagiarism detection. Together, all these AI-powered tools assist scholars in preparing clear, comprehensible,

and publication-ready academic documents with better efficiency and precision.

11.3.7 Phase V: Journal Selection and Submission

After the completion of a research paper, the last step is to select an appropriate journal. If the researcher fails to select a suitable journal, it often leads to desk rejection by the journal. AI tools used Natural Language Processing (NLP) to match the abstract against multiple journals. These tools support scholars by recommending appropriate journals and also deliver useful facts such as, impact factor, acceptance rates, indexing status of journal, scope alignment, and usual time to first decision. Numerous AI tools like IEEE Publication Recommender, Wiley Journal Finder, Elsevier Journal Finder, Scopus Journal Analyser, Edanz Journal Selector, MDPI Journal Finder, Scimago Journal and Country Rank (SJR), Taylor and Francis Journal Suggestor, Springer Journal Suggestor, JANE (Journal/Author Name Estimator) etc. guides researchers towards appropriate publication outlets. These tools increase submission efficiency and also enhance the prospect of effective publication.

11.4 Limitations and Ethical Concerns of AI In Research

Although there are numerous benefits of AI in research, yet use of AI in social science research presents quite a lot of limitations and ethical concerns which must be carefully addressed. One of the major limitations of this function is that AI models generally work as “black boxes” due to this it is very difficult for the researchers to understand how certain results are obtained which raises concerns about the transparency and reproducibility of the system. Moreover, there is the problem of data bias as AI systems rely completely on prevailing datasets which can reflect cultural, social, or institutional biases, leading to a skewed or prejudicial research conclusion. Besides this, when AI systems analyse primary datasets such as surveys, interviews or social media platforms, issues relating to data privacy and consent may also arise. Inappropriate handling of primary data can disrupt confidentiality and data protection rules. In addition, excessive dependence on AI in academic research rises numerous issues like plagiarism, originality of research and authorship ambiguity (Sharma, 2025). Hence, AI should be used to enhance the efficiency of research

in a more responsible and transparent way which can complement human expertise in research.

11.5 Conclusion

Integration of AI into research enhances the accuracy, efficiency and scalability of research as AI tools play a significant role in all phases of research – from collection, processing to advanced analysis of data, writing, journal selection as well as publication. AI tools reduce time and efforts of researchers that was put in empirical researches and enable researchers to focus more deeply on interpretation and theory building. AI tools enable scholars to extract structured data from unstructured sources, data cleaning, quicker detection of patterns, handling missing data, applying advanced statistical tools, bringing more clarity, coherence and citation management in academic writing and references. All these tools strengthen the overall quality of research results. Further, the journal selection and submission with AI tools also simplify the publication process and also reduces the chances of desk rejection. However, excessive reliance on AI tools can raise ethical issues such as data biasness, privacy related concerns, risk of academic integrity etc. Hence, there should be a balance between human researchers and intelligent systems as AI has the possibility to expand analytical insights, widen research horizons, and contribute towards policy making. Eventually, the effective combination of AI and human intellect can support the precision and applicability of social science research in this data-driven world.

References

- [1] Ali, M. Y., Naeem, S. B., and Bhatti, R. (2020). Artificial intelligence tools and perspectives of university librarians: An overview. *Business Information Review*, 20(10), 1–9. <https://doi.org/10.1177/0266382120952016>
- [2] Alordiah, C. O. (2023). Appreciating the AI Revolution: Empowering Educational Researchers Through AI Tools for Writing Research Articles. *Zamfara International Journal of Humanities*, 2(1), 178–195. <https://doi.org/10.36349/zamijoh.2023.v02i01.013>
- [3] Bhatnagar, P., and Bhatnagar, M. (2024). AI Tools—Facilitating Academic Research. *ANVESAK*, 54(1), 50–54. <http://103.66.72.15:9090/jspui/bitstream/123456789/490/1/3%20Ai%20tools.pdf>
- [4] Castillo-Martínez, I. M., Flores-Bueno, D., Gómez-Puente, S. M., and Vite-León, V. O. (2024). AI in higher education: A systematic literature

- review. *Frontiers in Education*, 9, 1–7. <https://doi.org/10.3389/feduc.2024.1391485>
- [5] Christou, P. (2023). How to Use Artificial Intelligence (AI) as a Resource, Methodological and Analysis Tool in Qualitative Research? *The Qualitative Report*, 28(7), 1968–1980. <https://doi.org/10.46743/2160-3715/2023.6406>
- [6] Floris, F. D., and Renandya, W. A. (2025). Artificial Intelligence Tools for Research Writing: Practical Tips for Teachers. *Teaching English as a Second or Foreign Language*, 29(1), 1–21. <https://eric.ed.gov/?id=EJ1478000>
- [7] Jackson, S. L. (2009). *Research Methods and Statistics* (3rd ed.). Wadsworth Cengage Learning.
- [8] Khalifa, M., and Albadawy, M. (2024). Using artificial intelligence in academic writing and research: An essential productivity tool. *Computer Methods and Programs in Biomedicine Update*, 5(2024), 1–11. <https://doi.org/10.1016/j.cmpbup.2024.100145>
- [9] Kothari, C. R. (2004). *Research methodology: Methods and techniques*. New Age International.
- [10] Pinzolit, R. F. J. (2023). AI in academia: An overview of selected tools and their areas of application. *MAP Education and Humanities*, 4, 37–50. <https://doi.org/10.53880/2744-2373.2023.4.37>
- [11] Sharma, N. (2025). AI-Powered research writing: Exploring research landscape. *Journal of Emerging Technologies and Innovative Research*, 12(4), 118–124. <http://www.jetir.org/papers/JETIR2504A14.pdf>
- [12] Venkatesh, V. (2022). Adoption and use of AI tools: A research agenda grounded in UTAUT. *Annals of Operations Research*, 308(1–2), 641–652. <https://doi.org/10.1007/s10479-020-03918-9>

Chapter 12

LEVERAGING ARTIFICIAL INTELLIGENCE TO TRANSFORM MARKETING PRACTICES

Gurleen Kaur

Assistant Professor, Department of Business Administration, Khalsa College for Women, Civil Lines, Ludhiana, Punjab, India-141001.

Email: gurleenbba28@gmail.com

Abstract

Artificial Intelligence (AI) has advanced as a revolutionary technology in various domains - finance, education, healthcare, robotics, entertainment, analytics, marketing and more. This chapter focuses on the role of artificial intelligence in the field of marketing and explores the various applications of this transformational technology to enhance efficiency and decision-making. AI has deepened its roots in the marketing world, extending from content creation, innovative ads, personalization, customer reach to aiding in building and maintaining better customer relationships. The uptake of AI-tools in various marketing functions such as customer analytics, digital advertising, content creation, and customer relationship management has accelerated as a result of increasing availability of big data and the advances in machine learning. This chapter attempts to study the role and impact of AI-driven marketing tools on the success of marketing attempts and performance of organizations drawing on various journal articles and scholarly publications. The adoption of artificial intelligence in marketing has been associated with improved customer experience, accurate targeting and elevated engagement levels. However, the literature also puts forward the significant concerns related to ethical use of technology and user data, privacy, algorithmic bias and issues of transparency and trust. AI in marketing can bring bankable profits overtime, but only if the 'what' and 'how'

is known, not neglecting the ethical factor so that adoption and implementation become seamless and successful.

Keywords: AI-Marketing, AI Trends, Ethical AI, Personalization, AI Applications

12.1 Introduction

Artificial Intelligence (AI) in marketing has emerged as an efficient and effective tool to level up the marketing efforts and performance. With increasing technological advancements, consumer awareness, dynamic demand behavior, and globalization of trade and commerce, it becomes imperative that organizations embed the AI tools in their operations and workflows, not only to sustain themselves in the business but also to obtain a competitive edge over other players in the market.

AI in marketing refers to the use of the capabilities of AI, like data collection, machine learning (ML), natural language processing (NLP), data-driven analysis, content generation, audience segmentation, and programmatic advertising, to automate marketing activities and decisions (Flinders et al., 2025). There are many tools available, such as GPTs, Jasper, Copilot, HubSpot, GrowthBar, Writesonic, Rytr, Simplified, etc., which can be used by content creators, advertisers, businesses, and organizations to aid in the process of embedding technology with their workflows and automating the operations.

In the current scenario, AI is being widely used in content generation and personalization, especially generative AI. The generative AI works by using deep learning neural networks, vector embeddings, and transformers to analyze the plethora of datasets and generate the response as per its learned dependencies and refine it further by iterating on it. This framework helps in the creation of highly personalized and customized responses catering to individual needs and improving customer experience (Divya et al., 2024).

A survey conducted by the management consultancy group McKinsey and Company found that 88% of the organizations globally are using AI in at least one of their business functions as of 2025, and 79% of the businesses are making use of gen AI (McKinsey and Company, 2025). They also found that the smaller companies are still to integrate AI deeply into their workflows as compared to larger

companies, which have reached the scaling phase, both in terms of revenue and employees. The survey also unfolded that the greatest revenue by integrating AI with different workflows was obtained in marketing and sales, strategy and corporate finance, and product or service development. It is evident from this survey that blending the AI with business has improved the efficiency and that its adoption can be seen widely irrespective of the scale of the organization.

12.2 AI Applications In Marketing

AI in marketing has been revolutionary as it can help a business reap multitude of advantages through its various applications (Haleem et al., 2022). Figure 12.1 highlights major applications.

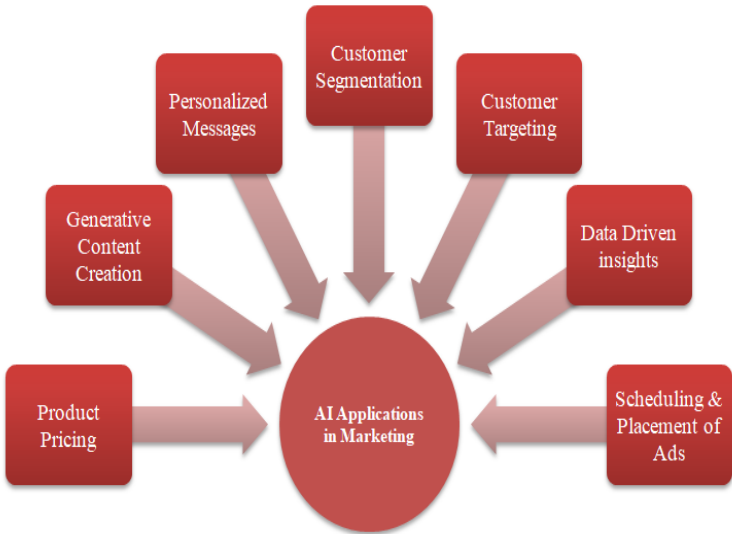


Figure 12.1: AI Applications in Marketing

12.3 AI Trends In Marketing

AI has changed the approach of marketers to conduct research and predict consumer behavior. It can provide more practical insights into the data, perform repetitive and data-driven tasks effectively, generate and accelerate revenue, and make the cumbersome tasks easier and efficient. Algorithms have made possible real-time customer engagement and interaction, analyzing the browsing history and purchase patterns to recommend in a personalized

manner. The function of a marketer is shifting from ‘reacting to consumer behavior’ to ‘predicting the consumer behavior’, all thanks to the revolutionary technology of artificial intelligence.

Today, AI is being used for advanced data analytics and hyper-personalization. AI can collect, process and analyze consumer insights, which further helps in predicting consumer preferences, thus facilitating customization. The chatbots and virtual assistants for addressing consumer queries and grievances and recommending as per customer requirement have made the buying experience more personalized and fulfilling for the consumers.

Through predictive analysis, natural language processing, machine learning and algorithmic processing, the marketers are able to tailor their advertising campaigns, understand the consumer more effectively and enhance their customer interaction and experience.

12.3.1 AI in Marketing Analytics and Decision Making

One of the most important applications of AI in modern marketing is the predictive analytics. As mentioned before, this tool has particularly helped the businesses to shift from ‘reaction’ to ‘proaction’ in the context of implementation of strategies. The machine learning algorithms look at past data, consumer behavior patterns, and market trends enabling the marketers to forecast market trends, customer behavior, and formulate marketing campaign and measure performance precisely. This capability helps marketers understand and manage the needs and use resources judiciously. Additionally, predictive analytics supports dynamic pricing strategies, where algorithms adjust prices based on competition, what customers are willing to pay, and demand forecasts. Figure 12.2 highlights customer predictive analytics using artificial intelligence.

Through the use of various AI tools and algorithms, the gigantic datasets can be analysed and this particular application of AI in marketing has helped the marketers to predict future trends and forecast the demand with accuracy and precision (Azuka et al., 2024). The most prominent and significant contributions of AI in the field of marketing is demand forecasting (Amosu et al., 2024).



Figure 12.2: How machine learning helps in customization

Source: Adapted from the research paper titled ‘Customer Predictive Analytics Using Artificial Intelligence’ (Zulaikha et al., 2020)

12.3.2 AI in Customer Relationship Management

AI, through its data and predictive analysis, machine learning and natural language processing capabilities, can understand the customer needs and emotions better, and the data available about the customers can be used by the marketers to build effective customer relationships.

Through chatbots, virtual assistants and customer service automation tools, AI in CRM has helped enhance responsiveness and customer satisfaction. Further, tools like voice recognition, augmented reality, along with predictive analysis, when integrated with CRM systems can help change the face of business-customer

interaction and relationship. This will ultimately lead to develop structured data, enhance automation, hyper personalization, and focus on sentiment analysis (Adesoga et al., 2024).

According to Finn and Downie (2024), customer trust is the new currency. With the help of new AI-based tools like actionable meeting summaries, personalized email templates and automated ticket routing, customer experience is now at the center of CRM depending upon the real-time data insights for personalized and timely interactions that customers expect.

12.3.3 AI in Personalization and Consumer Behavior

Murár (2023), in his study on Personalized Marketing with Artificial Intelligence, stated that AI can potentially improve tailored advertising and understand audience interactions in depth by leveraging data patterns. He states that by harnessing AI-tools, marketers tend to understand consumer behaviour better which leads to following advantages -

- Increased customer engagement
- Improved Conversion rates
- Higher customer lifetime value
- Deep understanding of the customer
- Increased Brand Loyalty

Prior to the digital era, the activity of personalizing marketing strategies was a taxing, manual job. The advent of digitalization and emergence of AI brought along with it a substantial amount of consumer data. The integration of AI and machine learning with marketing proved to be a significant turning point which brought the transition in the approach of marketers, shifting from reactive stance to a proactive anticipation by concentrating on individual customers rather than targeting broader consumer segments (Verma et al., 2021). All this has become possible due to the capabilities of AI to gather, collect, analyse humongous data derived from diverse sources, such as browsing histories, transaction records and social media interactions. (Apostol et al., 2024; Akil Khanov, 2024).

Oyekunle et al., (2024), in their qualitative and quantitative study, which aimed to examine consumer sentiments and trust dynamics when they interact with AI tools, stated that the adoption of AI

into business operations is a multifaceted process being influenced by various elements, such as, organizational leadership, culture, resources, perceived advantages, regulatory concerns, workforce preparedness, data security, technological capabilities, psychological considerations and contextual complexities.

12.4 Ethical Concerns Relating To The Use of AI

The emergence and incorporation of AI in the field of marketing have undoubtedly benefited the marketers fundamentally, strategically and even financially. It has elevated the customer experience as it attempts to understand their preferences and behavior much better than traditional methods. Despite its various advantages, AI is not free from certain concerns which surface in the form of privacy and security issues. The ethical concerns adjoined with AI pose a difficult challenge for its users to ensure and maintain the trust of the consumers. There have been many instances where the data security and safety of the consumers was compromised leading to personal information leakage. Many cases of algorithmic biases have been reported, which further questions the credibility and fairness of the use of various AI tools and methods. We live in an era where consumer trust is regarded as the superior, and any misuse of the consumer data, unintentionally or otherwise, will raise concerns about the AI and its applications. Any discrepancy or mishandling of consumer information creates a ripple effect and makes the masses wary of the methods of the organization.

Oyekunle et al., (2024), in their study reveal that the consumer views on AI are based on technological capabilities, psychological considerations and contextual complexities, and all of these including the organizational practices, are elemental in shaping the trust of consumers in AI.

This is where the concept of AI Ethics come into the picture, which, in the simplest terms, refer to the ethical use of AI ensuring the environmental and societal good.

Oluwafemi et al., (2021) advocated that companies that prioritize ethical AI practices build stronger and better relationships with the customers, enhance brand reputation, and avoid regulatory scrutiny, leading to not only the protection of consumer rights and

long-term business success, but also promoting a more responsible and sustainable use of Artificial Intelligence.

Hermann (2021), in his study reflected upon the five major principles of ethics in AI Marketing, namely - beneficence, non-maleficence, autonomy, justice and explicability. Beneficence corresponds to the promotion of overall well-being as well as social, environmental and common good. Non-maleficence focuses on the safety, security and privacy aspect along with prevention of risks and any harm, accidentally or deliberately, caused due to the use of AI. The tenet of Autonomy emphasizes on the balance between human and AI agency and decision-making power. Justice entails to fostering of fairness and avoidance of unwanted or unfair biases and discrimination, amending past inequalities and sharing of benefits and prosperity. Explicability corresponds to the intelligibility and accountability on how the AI systems work.

12.5 Conclusion

It won't be a hyperbolic statement that AI has transformed the face of marketing and its practices. It has proved elemental in restructuring and redefining the business landscape, helping the organizations in making data-driven decisions, engaging with customers and providing them with immersive, personalized experiences. AI has enabled the marketers to handle repetitive and cumbersome tasks with more precision and accuracy than before. Many businesses have already integrated the AI systems into their routine working and many are still adapting, so the shift and the pull towards the AI is undeniable, but at present, it can be said that AI is being underutilized. Owing to its complex and dearer nature, not all firms can afford AI tools. Another major concern that is on rise with regard to AI is breach of data privacy and security. Companies, in order to train their AI models, use the private data of the consumers which exploits their right to cyber privacy and safety. Algorithmic bias, unethical use, data leakage or pilferage and lack of transparency can substantially impeditment the use of AI and raise mistrust among consumers.

References

- [1] Adesoga, N. T. O., Olaiya, P., Obani, N. O. Q., Orji, U., Orji, A., and Olagunju, D. (2024). Leveraging AI for Transformative Business development: Strategies for Market analysis, Customer insights, and

- Competitive Intelligence. *International Journal of Science and Research Archive*, 12(2), 799–805. <https://doi.org/10.30574/ijrsra.2024.12.2.1291>
- [2] Akilkhannov, A. (2024). AI And Personalization In Marketing. *Forbes*. <https://www.forbes.com/councils/forbescommunicationscouncil/2024/01/05/ai-and-personalization-in-marketing/>
- [3] Amosu, O. R., Kumar, P., Ogunsuji, Y. M., Oni, S., and Faworaja, O. (2024). AI-driven Demand forecasting: Enhancing Inventory Management and Customer Satisfaction. *World Journal of Advanced Research and Reviews*, 23(2), 708–719. <https://doi.org/10.30574/wjarr.2024.23.2.2394>
- [4] Apostol, I. G., Prelipcean, M., Bostanica, E., and Munthiu, M. -C. (2024). A Data-Driven Approach: Assessing the Relevance of AI Algorithms in Tailoring Personalised Content for Social Media Users. *Proceedings of the International Conference on Economics and Social Sciences*, 6(1), 994-1003. <https://doi.org/10.24818/icess/2024/086>
- [5] Azuka, P., Ajiga, N. D., Olaoluwa, S., and Ezeigweneme, N. C. (2024). Predictive analytics for market trends using AI: A study in consumer behavior. *International Journal of Engineering Research Updates*, 7(1), 036–049. <https://doi.org/10.53430/ijeru.2024.7.1.0032>
- [6] Divya, D. V., and Agha Urfi Mirza. (2024). Transforming Content Creation: The Influence of Generative AI on a New Frontier. *Exploring the Frontiers of Artificial Intelligence and Machine Learning Technologies*. <https://doi.org/10.59646/efaimltc8/133>
- [7] Finn, T., and Downie, A. (2024). *AI in CRM (Customer Relationship Management)*, IBM. <https://www.ibm.com/think/topics/ai-crm>
- [8] Flinders, M., Hayes, M., and Downie, A. (2025, November 17). AI in marketing. *A guide to AI in marketing*. <https://www.ibm.com/think/topics/ai-in-marketing>
- [9] Haleem, A., Javaid, M., Qadri, M. A., Singh, R. P., and Suman, R. (2022). Artificial intelligence (AI) applications for marketing: A literature-based study. *International Journal of Intelligent Networks*, 3, 119–132. <https://doi.org/10.1016/j.ijin.2022.08.005>
- [10] Hermann, E. (2021). Leveraging Artificial Intelligence in Marketing for Social Good—An Ethical Perspective. *Journal of Business Ethics*, 179(1), 43–61. <https://doi.org/10.1007/s10551-021-04843-y>
- [11] Lparsons. (2025, April 14). *AI Will Shape the Future of Marketing - Professional & Executive Development* | Harvard DCE. Professional & Executive Development | Harvard DCE. <https://professional.dce.harvard.edu/blog/ai-will-shape-the-future-of-marketing/#Predictive-Analytics-and-Forecasting>
- [12] McKinsey and Company. (2025). *The state of AI: How organizations are rewiring to capture value*. McKinsey & Company. <https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai>

- [13] Murár, P. (2023). Bridging personalised marketing with artificial intelligence: An analysis of evolution and future trends. *Media & Marketing Identity*, 348–355. <https://doi.org/10.34135/mmidentity-2023-35>
- [14] Oluwafemi, I. O., Clement, T., Adanigbo, O. S., Gbenle, T. P., and Adekunle, B. I. (2021). A Review of Ethical Considerations in AI-Driven Marketing Analytics: Privacy, Transparency, and Consumer Trust. *International Journal of Multidisciplinary Research and Growth Evaluation*, 2(2), 428–435. <https://doi.org/10.54660/ijmrge.2021.2.2.428-435>
- [15] Oyekunle, D., Matthew, U. O., Preston, D., and Boohene, D. (2024) Trust beyond Technology Algorithms: A Theoretical Exploration of Consumer Trust and Behavior in Technological Consumption and AI Projects. *Journal of Computer and Communications*, 12, 72- 102. <https://doi.org/10.4236/jcc.2024.126006>
- [16] Verma, S., Sharma, R., Deb, S., and Maitra, D. (2021). Artificial intelligence in marketing: Systematic review and future research direction. *International Journal of Information Management Data Insights*, 1(1), 100002. <https://doi.org/10.1016/j.jjimei.2020.100002>
- [17] Zulaikha, S., Mohamed, H., Kurniawati, M., Rusgianto, S., and Rusmita, S. A. (2020). Customer Predictive Analytics Using Artificial Intelligence. *The Singapore Economic Review*, 70(4), 1009–1020. <https://doi.org/10.1142/s0217590820480021>

Chapter 13

ARTIFICIAL INTELLIGENCE (AI)- POWERED ACCOUNTING IN INDIA: APPRAISING SOFTWARE SOLUTIONS, THE PERKS AND COMPARATIVE BENEFITS OVER CONVENTIONAL METHODS

Jasmeet Kaur^{*,1} & Sukhvinder Kaur²

¹Assistant Professor, Chandigarh University, Mohali, India-140413.

²Assistant Professor, Khalsa Institute of Management and Technology for Women, Civil Lines, Ludhiana, Punjab, India-141001.

*Email: jasmeet.e19242@cumail.in

Abstract

The unification of Artificial Intelligence (AI) into accounting procedures represents an apex shift in the practice in which financial information is captured, processed and reported, especially within emerging economies like India. This chapter undertakes a holistic appraisal of the effect of Artificial Intelligence on classical accounting practices. The study analyzes the implementation of AI-powered accounting tools such as Tally Prime, Zoho Books and Vyapar Taxonevia application programming interfaces (APIs) and robotization modules. Additionally, data has been gathered from various transnational corporations such as Deloitte, Amazon and Unilever and indicate the use of Artificial Intelligence in automated data entries, bank reconciliation, tax research and fraud detection. Secondary data were sourced from various industry reports, academic studies, and business publications to evaluate performance differentials between conventional and AI-based financial reporting. The findings also reveal that there is a substantial change in the role of book-keeping professionals to more strategic and analytical role, resulting in inclusive corporate

financial intelligence. Despite the fact that Artificial Intelligence has proven superior to Human Intelligence, as it requires huge amount of data, the research shows that the future of accounting is a hybrid system requiring human accountants to perform professional judgments and ethical decision-making tasks, while Artificial Intelligence performs routine and analytical tasks. This amalgamated approach represents the best accounting model for contemporary Indian organizations.

Keywords: Artificial Intelligence, Accounting Procedures; Ai-Powered Accounting Software; Human Intelligence, Indian Accounting System

13.1 Introduction

13.1.1 Background and Context

The accounting profession has experienced a spectacular change in the last ten years that has seen the manual ledger system giving way to advanced digital platforms. Regulatory changes, especially the introduction of the Goods and Services Tax (GST) in 2017, the process of digitalization provided by the Digital India project, and the growing complexity of business processes have accelerated this change in India. The COVID-19 crisis only enhanced the trend in favor of cloud and automated accounting products, as remote work became the new standard and all businesses were in search of operational resilience.

The technologies of Artificial Intelligence, including machine learning (ML), natural language processing (NLP), robotic process automation (RPA), and optical character recognition (OCR) have become a paradigm in the accounting field (Kokina and Davenport, 2017). These technologies allow systems to be learned based on data trends, take intelligent decisions, automate routine actions, and give predictive information that previously could not exist with traditional solutions.

13.1.2 The Indian Accounting Environment

The accounting ecosystem in India is different and distinctive with the various types of business structure such as micro-enterprises, large multinational companies, complicated tax rules such as GST with

multiple tax categories and a high population of small and medium enterprises (MSMEs) which contribute to about 30 percent of the GDP in India. In India, traditional accounting has been controlled by such software as Tally that controls 70-80 percent of the market share of SMEs, as well as, international solutions such as QuickBooks and Zoho Books (Goenka, 2024; Srinivasan, 2021). The traditional approach is challenged, however, by the following issues:

- Entering data manually that caused financial differences.
- Delays in reconciliation process which consumes a lot of human resource.
- Inadequate real-time information on financial positions.
- Complexity of compliance of tax regulations and changing GST regulations.
- Scalability problems with business expansion.
- Human resource limitation especially of small firms.

13.1.3 The AI Revolution in Accounting

In 2026, market research found that compared to the global average of 52% of businesses intending to use AI in their accounting processes, 73% of businesses in India plan to do so, making India a global leader. This aggressive adoption pattern shows the opportunities and the needs that are fueling digital transformation in the Indian businesses.

The AI-driven accounting systems solve the underlying weaknesses of the traditional approach by:

- Improving the process of data entry and transaction categorization to 95% accuracy (Davenport and Ronanki, 2018; Kokina and Davenport, 2017).
- Offering real-time financial data and dashboard.
- Predictive cash flow analytics.
- Automation of sophisticated compliance process such as GST reconciliation.
- Identifying anomalies and fraud using pattern recognition.

With India being an up-and-coming economy that is projected to become the third-largest economy in the world in 2027, both the digital infrastructure in India and the utilization of India Stack have grown substantially, as evidenced by the implementation of

India Stack-based e-invoicing requirements and the adoption of the Goods and Services Tax (GST) e-invoicing requirement as mandatory (International Monetary Fund, 2023; National Payments Corporation of India, 2022). This digitalization has required the abandonment of the traditional, manual-based book-keeping practices to a complex AI-based financial ecosystem. Making AI a part of accounting is not an upgrade to the technology but an apex shift in the capture, processing, and utilization of financial data in strategic decision-making (Gupta and Kumar, 2025).

According to the statistics provided by the Ministry of Electronics and Information Technology (MeitY) in 2025, it was reported that the use of digital economy has increased operational efficiency in the financial sector by more than 40 percent as compared to the 2020 baselines. The purpose of the study is to examine the adoption of AI-based accounting software in India and to evaluate the advantages and the benefits of AI-based accounting systems. Comparison of the use of AI-powered solutions to the traditional accounting processes on various parameters has been made. The research design adopted in this chapter is a qualitative and analytical study design that utilizes secondary data. The data has been collected from various sources like Industrial reports, academic journals, company case studies and various business publications. Based upon the various sources, an accounting model needs to be developed that is a hybrid of AI and human and fits Indian business organizations.

13.2 Literature Review

- Davenport and Ronanki (2018) divide the applications of AI into process automation, cognitive insight, and cognitive engagement. Their research notes that the majority of the successful AI applications in finance are to automate repetitious tasks- consistent with the patterns of AI adoption in Indian SMEs.
- Davenport (2023) presents the idea that AI can help organizations transition to the stage of descriptive analytics to prescriptive and predictive analytics. Their model offers a basis on which AI-related decision-making in accounting set-ups can be comprehended.
- Marr, B. (2024) identifies practical uses of AI and machine learning in industries and explains how automation and

anomaly detection, as well as intelligent forecasting, help companies to enhance efficiency in their work.

- The Stanford Graduate School of Business (2025) report on Human + AI in accounting also indicates that AI supplements accountants and re-purposes them to include advisory and strategic roles. It determines the new competency needs, and this is very pertinent to the Indian accounting population.
- Chowdhury (2025) uses the Technology-Organization-Environment (TOE) framework to investigate the adoption of AI in Bangladeshi and Indian companies and states that organizational readiness and regulatory support are crucial factors in this matter.
- International Federation of Accountants (2025) dictates in their international policy views that it is necessary to make AI governance and professional skepticism in automated settings responsible.
- Ministry of Electronics and Information Technology (2025) also identifies AI and digitalization as two forces behind the trillion-dollar digital opportunity in India, which can enable an accounting automation ecosystem.
- Tally Solutions Pvt. Ltd. (2025), AI is used to record Tally Prime, such as automated data entry, intelligent reconciliation, and compliance warnings.
- Vyapar Tech (2026) also notes the benefits of automation to Indian retailers.
- Zoho Corporation (2026), Zia is a smart automation tool that is incorporated in Zoho Books, which improves forecasting and anomaly detection.
- Bendal et al. (2026), practitioners discuss perceptions of AI as a disruptive technology and conclude that efficiency benefits are acknowledged by professionals, but they have worries about job loss and skill obsolescence.

13.3 Artificial Intelligence-Based Accounting Software Solutions IN INDIA

The table 13.1 highlights the classification of AI-based accounting software in India.

Table 13.1: AI-Based Accounting Software Classification in India

Cate- gory	Soft- ware / Plat- form	Key Features	AI Capabilities	Target Users
India-Specific AI Ac- counting Plat- forms	Suvid	GST compliance, data automation, reconcilia- tion	Automated data extraction and document processing	SMEs, ac- countants
	AI Ac- countant	Smart book-keeping, tax automation	AI-driven financial insights and error detection	Startups, small firms
	Febi.ai	Invoice manage- ment, expense tracking	Predictive ana- lytics and auto- mated catego- rization	SMEs
	F-ai	Financial automation tools	AI-based forecasting and anomaly detection	Busi- nesses
	His- abkitab	Simple accounting, mobile-friendly	Basic AI for ex- pense tracking and reminders	Micro busi- nesses
Built-in AI-Based Plat- forms	Tal- lyPrime	Accounting, inventory, GST man- agement	Smart reporting and automation insights	SMEs, en- terprises
	Zoho Books	Cloud accounting, invoicing	AI assistant and predictive analysis	SMEs, free-lancers

Continued on next page

Table 13.1 (Continued)

Cate- gory	Soft- ware / Plat- form	Key Features	AI Capabilities	Target Users
	Vyapar	Billing, inventory, GST	AI-based business insights and automation tools	Small busi- nesses
Interna- tional Plat- forms Adapted for India	Quick- Books Online	Cloud accounting, GST compliance	AI-powered reporting and expense categorization	SMEs
	Xero	Online accounting, bank integration	Machine learning for reconciliation and forecasting	Growing busi- nesses
	Digits	Financial analytics, reporting	AI-driven insights and performance tracking	Enter- prises
Enterprise- Level AI Solu- tions	Focus X ERP	ERP with accounting modules	AI analytics and workflow automation	Large organiza- tions
	SAP (with AI mod- ules)	Enterprise resource planning	Advanced AI for forecasting and fraud detection	Corpo- rates
	Oracle Cloud (AI- enabled)	Cloud ERP, financial manage- ment	AI-driven automation and predictive analytics	Large en- terprises

Following are the widely used software in Indian context (Davenport and Ronanki, 2018):

13.3.1 Tally Prime

With a large market share in India and a successful flagship product called Tally Prime, Tally Solutions has transformed it into a powerful AI-based product. Tally Prime supports “TallyAI,” a compliance automation module, as of version 7.0 of late 2025. Another notable aspect is the so-called Connected GST functionality that recognizes GST Identification Numbers (GSTINs) in real-time and warns about the possibilities of a mismatch in Input Tax Credit (ITC) prior to filing (Tally Solutions, 2025). The AI used by Tally also supports Tally Smart Ledger Creation which recommends ledger groups, tax settings according to the type of description being added to the account, greatly shortening the amount of time it takes to set up new accountants. Tally Prime has also added an option of “Auto-Bank Reconciliation” that retrieves bank statements through the API and employs fuzzy logic matching to reconcile transactions among the cases when reference numbers or dates do not coincide, as is usual in the Indian banking environment.

13.3.2 Zoho Books

Zoho Books uses its own AI-based assistant, named Zia to provide a more cloud-based and automated experience. Zia is a virtual financial assistant, which is able to receive voice commands and give answers in conversation (e.g., “Zia, what is my cash flow position this week?”). The software parses through emails that come in and find invoices in the email, employs highly advanced OCR to retrieve data, drafts a bill and directs the bill to go through approval according to what has been learned about the organizational structures (Zoho Corporation, 2025; Davenport and Ronanki, 2018). Zoho also has a predictive analytics engine that forecasts cash flow variance based on the payment behavior of its customers and provides a score of payment probability of overdue invoices.

13.3.3 Vyapar and Suvit Integration

Vyapar, which was initially aimed at the micro-business sector, took a major strategic step by acquiring and integrating Suvit, an AI-banking automation service. This has made AI more democratic to the smallest of traders. The major value statement is that it automates the process of data entry in diverse forms. Indian merchants are frequently

invoiced in an uncommon format (images, WhatsApp pictures, handwritten notifications). Vyapar-Suvit integration is an AI-based advanced vision-based integration to digitalize these unstructured documents with high accuracy. The solution is especially affordable, and it has a business model that reduces the barriers to the entry of AI in Tier-2 and Tier-3 city businesses ((NASSCOM, 2023).

13.4 Advantages of AI Compared To The Traditional Approaches

The advantages of AI based accounting over traditional ones can and are quantifiable, specifically in their precision, effectiveness, and risk mitigation.

a. Accuracy of Automated Data Entry: It will be based on the accuracy of the machines and the quality of the data entry operators. Traditional data entry has about 1-4 error rate possibility. By contrast, 2026 AI-based OCR and IDP systems have reached the accuracy rates of above 99%. Through automation of the invoice data capture, the businesses minimise the errors of the fat fingers that plague manual accounting (Kokina and Davenport, 2017). In 2025, the Institute of Chartered Accountants of India (ICAI) conducted a study that found that companies that employed AI tools said that time on data entry had been reduced by 75-80 percent, enabling their staff to shift their efforts to verification and analysis processes.

b. Efficiency of Bank Reconciliation: Bank reconciliation was a very boring task that was carried out once a month. AI makes this a process that is not isolated. Algorithms are aligned to the real-time transactions and deal with complicated situations like combined payments or currency conversions. According to industry reports, it takes time to reconcile information in organizations that adopt AI tools such as Zoho Books or Tally Prime; this has been reduced by 75 percent. This productivity not only saves the labor hours, but also guarantees the books to be in always audit-ready condition.

c. Tax Compliance and Research: Compliance is a big burden in the intricate Indian GST regime. The advantages of AI are dramatic in this case. AI systems will be able to cross-check the availability of Input Tax Credit (ITC) on government portals (GSTN) in real time, ensuring that no claims to invalid or mismatched invoices are made. Such proactive compliance minimizes the possibility of punishments.

Moreover, AI research tools are able to scan through a new tax notification of thousands of pages to draw attention to any changes in a particular industry, which would take a human expert day to accomplish.

d. Fraud detection: What is perhaps the most important advantage is fraud detection. Traditional internal controls are based on periodic audit and random sampling. AI allows for “Continuous Monitoring”. The systems of anomaly detection generate an expectation of normal behavior of each user and vendor. Should an entry not confirm to this pattern such as an entry relating to payroll at 2:00 AM on Sunday, or a duplicate payment of an invoice to a vendor with an insignificantly different bank account number, the system will immediately raise a red flag. Recent statistics indicate that AI systems are capable of identifying fraudulent trends with 40-50 superior effectiveness in comparison with conventional rule-based measures (Association of Certified Fraud Examiners, 2024).

e. Real-Time Reporting: AI removes the latency between the time of an event in the financial sector and when it is reported. The traditional processes tend to lead to a month-end close process that bleeds into the middle of the next month. AI-based systems help achieve a continuous close, which allows the management to see P and L and Balance Sheets in real-time. Monthly close cycle is 7.5 days shorter on average in organizations that use these technologies as compared to those that do not (Stanford GSB, 2025).

Thus, AI democratizes accounting, lowers the art of doing routine accounting.

13.5 Applications In Multinational Companies

The key Indian transnational companies engaged in artificial intelligence development have been on the frontline to implement high-end AI systems, which in many cases, have created proprietary solutions that act as a standard of efficiency.

A. AI Initiatives of Deloitte in India

Deloitte India was the first to use Generative AI in taxation with its product called Tax Pragma.

Table 13.2: Comparison of Conventional Accounting and AI-Powered Accounting

Aspect	Conventional Method	AI-Powered Method	Verdict / Outcome
Data Entry and Processing	Invoices, receipts and transactions are entered manually through typing or spreadsheets. Error rate is approximately 1–4%. A person can process around 100–200 transactions per day. Repetitive work increases the possibility of fatigue-related errors.	Documents are captured automatically using OCR, email integration, digital document processing and bank-feed synchronization. Error rate is typically below 0.5%, while more than 10,000 transactions can be processed per hour.	AI is approximately 50–100 times faster and 5–8 times more accurate.
Categorization of Transactions	Account codes are selected manually based on the accountant's knowledge and judgement. Different users may classify transactions differently. Supervision is required and each transaction typically takes 30–60 seconds.	Machine learning automatically categorizes transactions using historical data and continuously improves classification. Multi-dimensional categorization is completed in less than one second.	AI improves speed by about 30–60 times while providing greater consistency.
Bank Reconciliation	Ledger accounts are matched manually with bank statements, usually through spreadsheets. Each account may require 4–8 hours per month and errors or omissions are common.	Transactions are matched automatically using intelligent fuzzy matching. Exceptions are highlighted automatically and reconciliation usually takes only 5–15 minutes per account.	AI reduces reconciliation time by approximately 90–95%.
Financial Reporting	Reports are prepared manually with month-end closing taking 7–15 days.	Reports are generated automatically in real time with customizable dashboards,	AI transforms reporting

Continued on next page

Table 13.2 (Continued)

Aspect	Conventional Method	AI-Powered Method	Verdict / Outcome
	Reports are static and require specialized accounting expertise.	natural-language queries and self-service analytics.	from periodic to real-time.
Compliance and Taxation	GST calculations, reconciliation and return filing are performed manually. Regulatory updates are monitored manually, increasing the risk of errors and penalties.	Tax calculations, GST reconciliation and return filing are automated. Regulatory changes are updated automatically with built-in validation.	AI reduces compliance effort by about 60–70% while minimizing filing errors.
Audit and Verification	Audit relies on manual sampling and document review, requiring approximately 2–4 weeks of preparation.	AI analyses all transactions, detects anomalies automatically and provides electronic audit trails. Audit preparation is reduced to about 1–3 days.	AI saves approximately 80–90% of audit preparation time while improving audit coverage.
Fraud Detection	Fraud is detected reactively through manual review with limited pattern recognition. Detection rates are generally around 30–50%.	Continuous monitoring with AI detects anomalies and suspicious transactions in real time while learning from historical fraud patterns.	AI improves fraud detection by about 40–60%.
Cost Structure	Initial investment is relatively low, but recurring expenses for staff, infrastructure, paper records and error correction are high.	Initial investment is moderate to high because of software, training and data migration. However, recurring costs are substantially lower owing to automation and paperless workflows.	Although AI requires higher initial investment, it reduces overall operating costs by approximately 30–50% over time.

Introduced widely in its offices in India, Tax Pragya uses Large Language Models (LLMs) that are trained on Indian tax case laws, tax notifications, and circulars. It helps consultants by aiding with research of pre-tax and writing answers to tax notification, and estimating the results of possible litigation. Also, Deloitte implements DART bot and the Omnia audit platform. Omnia is based on machine learning that analyzes 100% of journal entries (not a sample) of a client to detect anomalies and detect risk patterns that can go unnoticed by human auditors. Such transformation of the sampling to the full-population testing is a paradigm shift in the audit methodology (Deloitte, 2026).

B. Accounting Automation of Amazon

The accounting practices of Amazon India are a test of the size of the AI automation. Manual reconciliation is not possible because of handling millions of transactions per day. Amazon is powered by a proprietary FinAuto system that is AI-driven. Reconciliation of vendors is done through this system where the purchase orders, goods receipt notes, and the vendor invoices are matched automatically and in real-time. In the event of a mismatch such as a variance of 50 in the price in a bulk order, the AI will check within a pre-set tolerance limit and approve or warn the customer to consider the discrepancy. The management by exception model enables Amazon to close its books within hours after the end of the month, which usually takes weeks.

C. Unilever's AI Applications

Hindustan Unilever Limited (HUL) applies AI in its SAP environment to transform supply chain finance. Their intelligence modules estimate the budgeting needs of the marketing and distribution based on the analysis of divergent data, such as weather patterns, festive schedules, and past sales details. Also, Unilever applies AI to the process of accounts payable in Touchless Invoicing. The system reads invoices of thousands of distributors, matches them to delivery data and makes payments automatically with no human intervention, maintaining good working capital cycles of its supply chain partners (Hindustan Unilever Limited, 2023).

13.6 Accounting Professionals Have A Role Transformation

The adoption of AI is heralding a radical change in professional identity of the accountant. The position is moving out of being a scorekeeper, which is concerned with capturing past transactions, to a strategic partner. The book-keeping, vouching and ticking as routine tasks are increasingly being done through software in the Indian context. This sets the Chartered Accountant (CA) and the finance professional free to be involved in more valuable work (Davenport and Ronanki, 2018).

This change demands a new competency. The knowledge of debit and credit rules is no longer essential compared to “AI Literacy” becoming an integral part of it. In 2026, accountants will have the knowledge of data architecture, control the implementation of AI software, and interpret the complex predictive analytics. The accounting firm is no longer going to be selling on the basis of value that the company will do your debt returns correctly but on the basis that we will utilize your financial information to enable you to grow (International Federation of Accountants, 2023). The professional judgment takes precedence; though AI may be able to point out an anomaly, it is up to a human being to comprehend the business environment and ethical consequences of the anomaly. The profession is therefore getting more appealing to the talent looking into strategy and data science, leaving behind the image of boring data crunching.

13.7 The Hybrid Model: Future of Accounting

In India, a Hybrid Model is clearly in the future of accounting, as the research reveals. Full manual dependency and complete automation are both not possible. The Hybrid Model uses the computation power of AI in scenarios where there are large volumes, repetitive and rule-based work (data entry, reconciliation, first-level compliance check) and instead leaves work that need finesse, negotiation, ethical judgment, and problem-solving to the human intelligence. This model positions the AI as the Co-pilot. The pilot is the human accountant, who determines the destination (strategy), the instruments (AI dashboards), and manual control during a turbulent situation (crisis management or complex litigation). This cooperation makes the

most out of efficiency and lessens the risks of an algorithmic bias or error. To the Indian organizations, it will imply investing in AI tools that are not aimed at filling their jobs, but it will be an addition enabling the smaller workforce to utilize larger amounts of work more precisely (International Federation of Accountants, 2023). This combined system is the most viable way to go as it offers equilibrium between technological efficiency and professional responsibility.

13.8 Conclusion

The introduction of Artificial Intelligence into the Indian accounting practices is a separation point in the history of this profession. Introduction of Artificial Intelligence into the accounting process is not only a technological progress, but it is also a total reconsideration of the purpose and value of the accounting function. Accounting shifts with strategic intelligence, moving forward looking, as opposed to record keeping, competitive advantage instead of compliance burden, and value creator instead of cost center.

This chapter has determined that AI-based applications such as Tally Prime, Zoho Books, and dedicated solutions applied by multinational companies have incontrovertible advantages compared to traditional ones, which cover higher accuracy, real-time accounting, and detecting fraud. The benefits in terms of time saved in closing and a percentage decrease in the error rates are an attractive business argument in favor of adopting it. Technology is however not a panacea. The future is of the so-called Hybrid Accountant a specialist who integrates technical accounting skills with digital literacy. As Indian business further transforms into a digital realm, human judgment and artificial intelligence will be used to determine financial excellence. The education system, regulatory agencies such as ICAI and organizations must adopt this transformation as it creates a culture of AI enabling the accountant to rise to the position of a full-fledged strategic advisor.

In the case of India, where the economy is ambitious, its regulatory environment is intricate, and the MSME sector is huge, AI-powered accounting is not a luxury, but a necessity. It makes high-level financial management more democratic, even the playing ground between small and large business equal, and millions of enterprises are able to operate with efficiency and insight previously accessible

solely to big corporations. It is not a question whether to use AI in accounting, but when and how fast it can be done. The competitive advantage of early adopters is currently open but it would decrease when adoption becomes universal. Today, decisive action by organizations and professionals will make them the future leaders; the waiters will be on the losing end. The future of accounting in India is intelligent, automated, real-time, and strategic and the future is here.

13.9 Predictions For 2030

The combination of artificial intelligence (AI) and digital technologies is likely to greatly change the future of accounting. International Federation of Accountants (2023) says that AI is being introduced into the accounting processes at an accelerated rate especially in businesses that have a high turnover. It is estimated that most of the Indian companies that had a turnover of more than Rs.5 crore will integrate AI in over 80 percent of their accounting processes.

Accounting procedures are supposed to become completely automated and manual accounting is not required. This is consistent with the results of Davenport and Ronanki (2018), who have stressed that AI technologies are mostly applied to the automation of the processes, which means that humans are involved less in repetitive work. Consequently, the impact will be the realization of real-time financial reporting where monthly closing processes will be a thing of the past.

Moreover, the accounting professionals are expected to change considerably, their tasks will be more of entry-level but less of the analytic and advisory ones. Research indicates that accountants can be engaged in decision-making and strategic advisory control as much as 70 per cent and over, as opposed to roughly 30 per cent currently. This shift relates to the increased significance of the cognitive insight and engagement applications of AI as emphasized by Davenport and Ronanki (2018). Another issue that is described by the International Federation of Accountants (2023) is the fact that automated regulatory reporting will interlink accounting systems with government platforms and lead to the decrease of compliance burdens.

Additionally, natural language processing will enable accounting systems to be controlled by voice and conversational controls. The growing competition and commoditization of AI tools are likely to reduce the barriers to entry and such technologies will be accessible even to small and medium enterprises. Finally, accounting systems will be modified to be more descriptive and predictive and prescriptive, which will allow making decisions in advance.

13.10 Recommendations

So as far as Small and Medium Businesses are concerned: A gradual shift is required that should begin now - Start with cloud-based AI accounting without necessarily being happy with the manual processes. Learning curve and benefits increases with time.

- Select the right option - In the case of businesses with a turnover of less than 1 crore: Zoho Books, Febi.ai, or Vyapar. Between 1-10 crore: TallyPrime, Zoho Books or AI Accountant. Over 10 crores: Suvit, full-fledged ERP, or enterprise.
- Invest in training- Spend 15-20 percent software budget on intensive staff training and change management.
- Introduce gradually - Initially implement one module (e.g. expense tracking or invoicing), and prove its success, and then increase.
- Calculate and report ROI - Measure time savings, eliminate errors and efficiency improvements to maintain ongoing investment and involvement.
- To the Chartered Accountants and Accounting Professionals
- Become technology adopters – AI applications are not a menace to professional relevance because they add to but not replace tedious tasks and allow strategic advisory to be realized.
- Upskill on a consistent basis - Lasting 10-15 hours per month to learning about AI tools, data analytics, and technology trends. Take into account official qualifications.
- Transform service model - Change the compliance-driven and transaction-oriented services to advisory-oriented strategy services. The time saved by automation can be used to do more valuable work with clients.

- Strategic specialization- Become an expert in specialized fields (such as industries, advanced analytics or application of technology), consulting.
- Be the leader of client change Customer behaviours: No longer a bookkeeper, but a leader who guides the client toward transformation in a digital world.
- For Software Vendors
- Focus on the user experience -Features come secondary to simplicity and intuitive features. Architecture to non-technical users.
- Invest in localization multi-language support, regionalization, workflows and works specific to India, and full GST compliance.
- Deliver superior service - Implementation support, training materials, customer support and change management support.
- Transparent AI - Explainable Algorithms, Audit trails and options to build trust through human-in-the-loop.
- Neutral prices, flexible pricing - Subscription plans, pay as you grow plans and low entry fees to small businesses.

References

- [1] Alarcon, M., Ng, C., and McBride, K. (2021). Artificial intelligence in accounting: Opportunities and challenges. *Journal of Emerging Technologies in Accounting*, 18(1), 1–15. <https://doi.org/10.2308/JETA-2020-055>
- [2] Amazon India. (2025). *Operational excellence report: Vendor management and FinAuto*. Amazon Corporate Communications.
- [3] Association of Certified Fraud Examiners. (2024). *Report to the nations: Global study on occupational fraud and abuse*.
- [4] Bendal, A., and Planas-Sabasa, S. A., Atento, R. G., Espelita, C. A. M. H. (2026). Artificial Intelligence as Disruptive technology in accounting: A Qualitative Study of Practitioner Perceptions on Automation, Judgement, and Decision Support. *Journal of Enterprise Strategy and Management Innovation*, 39(2), 112–130. <https://doi.org/10.65166/0sdayg70>
- [5] CPA Australia, and Associated Chambers of Commerce and Industry of India. (2024). *Business technology report 2024*.
- [6] Chowdhury, F., Latiff, A. R. A., and Mahmood, R. (2025). Adoption of Artificial Intelligence Accounting Systems in Bangladeshi Accounting Firms: TOE Framework and Country-Specific Variables. *International Journal of Business and Management*, 20(4), 262. <https://doi.org/10.5539/ijbm.v20n4p262>

- [7] Davenport, T. H. (2023). *The AI advantage: How to put the artificial intelligence revolution to work*. MIT Press.
- [8] Davenport, T. H., and Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, 96(1), 108–116.
- [9] Deloitte India. (2026). *The future of tax and audit: Strategic advantage through GenAI*. Deloitte Insights.
- [10] Goenka, T. (2024). How Tally, bookkeeper to India's MSMEs, is harnessing AI. *Mint*.
- [11] Gupta, R., and Kumar, S. (2025). Artificial intelligence and accounting practices: An academic perspective. *Information Analytics and Big Data*, 9(1), 45–62. <https://doi.org/10.1057/s41599-025-05004-6>
- [12] Hindustan Unilever Limited. (2025). *Annual report 2024–25: Digital transformation*.
- [13] International Monetary Fund. (2023). *India's economic outlook and growth projections*. IMF.
- [14] Institute of Chartered Accountants of India. (2025). *Digital competency maturity model for professional accounting firms (Version 2.0)*.
- [15] International Federation of Accountants. (2025). *AI and intelligent automation in accounting: Policy perspectives*.
- [16] Kokina, J., and Davenport, T. H. (2017). The emergence of artificial intelligence: How Automation is Changing Auditing. *Journal of Emerging Technologies in Accounting*, 14(1), 115–122. <https://doi.org/10.2308/jeta-51730>
- [17] Marr, B. (2024). *A practical guide to artificial intelligence*. Wiley.
- [18] Ministry of Electronics and Information Technology. (2025). *Trillion-dollar digital opportunity: Annual report 2024–25*. Government of India.
- [19] National Payments Corporation of India. (2022). *India stack and digital financial infrastructure*.
- [20] NASSCOM. (2023). *Artificial intelligence adoption in Indian SMEs*.
- [21] Srinivasan, S. (2021). Tally solutions: Homegrown and growing big. *Financial Express*.
- [22] Stanford Graduate School of Business. (2025). *The HumBorg report on human + AI in accounting*.
- [23] Suvit Technologies. (2024). *AI-powered bookkeeping automation and document digitization*.
- [24] Tally Solutions. (2025). *TallyPrime release notes: AI capabilities*.
- [25] Vyapar. (2026). *How Indian retailers will change with automation*.
- [26] Zoho Corporation. (2026). *Zia: Intelligent automation for modern enterprises*.

NOTES

This image shows a single sheet of white paper with horizontal ruling lines. The lines are evenly spaced and run across the width of the page. There are no margins, text, or other markings on the paper.

Chapter 14

ROLE OF ARTIFICIAL INTELLIGENCE IN THE BANKING SECTOR: A SYSTEMATIC LITERATURE REVIEW

Noel Parge & Jisha Alwin

Principal, B.P.H.E. Society's Ahmednagar College, Ahmednagar, Maharashtra, India-414001.

Research Scholar, B.P.H.E. Society's Ahmednagar College, Ahmednagar, Maharashtra, India-414001.

Email: rosyjoseph2001@gmail.com

Abstract

The growing digitalization of the financial service sector and rising customer expectations have encouraged the use of artificial intelligence (AI) in the banking industry to boost efficiency, security, and decision-making. This paper will seek to understand how AI is changing the way banking is conducted and the effect of AI on customer experience, risk management and regulatory compliance. The systematic literature review (SLR) was used to examine recent academic literature on the applications of AI in banking. The results suggest that AI is useful in boosting operational efficiency, fraud detection, credit scoring, financial inclusion, and the quality of services. The AI helps to bring about wider contributions to society, such as financial inclusion and confidence in the financial system through more accessible, secure, and personalized banking services.

Keywords: Artificial Intelligence, Systematic Literature Review, Banking Sector

14.1 Introduction

The banking industry is experiencing a paradigm shift in the world due to the rapid change in the field of artificial intelligence (AI)

and more sophisticated digital technologies. The growing number of online transactions, the use of mobile and online banking, and the growing customer needs to be served with personalized and immediate services have forced banks to redefine the conventional ways of operation. Machine learning-based AI, deep learning, natural language processing, and predictive analytics technologies are gradually integrated throughout the banking operations to increase the accuracy of decision-making, automatize routine and complicated processes, and make the entire process more valuable to the end customer. The technologies help banks to process large amounts of structured and unstructured data to make more informed strategic decisions, assess risks better, and engage customers in a very competitive financial setting.

Simultaneously, the AI integration into the banking processes creates some serious management, ethical, and regulatory issues. Due to the impact of AI systems on crucial processes, including lending, fraud detection, customer-facing, and compliance, issues of data privacy, algorithmic discrimination, transparency, and responsibility have been in the focus. The trust, explainability, and fairness of the system heavily depend on the use of automated systems, especially when the financial stability and customers are directly dependent on the use of AI-driven decisions. Governmental bodies and financial institutions are thus paying much attention to setting up well-built governance mechanisms that would make AI technologies be used responsibly and with good ethics. It is necessary to have an overall knowledge of the role of AI in the banking section to balance innovation and risk management, financial inclusion, enhanced regulatory compliance, and sustainable growth in the changing digital banking environment.

14.2 Review of Literature

14.2.1 Customer Experience and Relationship Management

Several studies have emphasized the role of artificial intelligence in enhancing customer experience and strengthening relationship management in the banking sector. Abed et al., (2025) explained that AI applications help banks reduce customer churn, improve customer satisfaction, and strengthen customer trust through personalized services and strategic forecasting of customer needs. Similarly, Lülök

and Sebestyén (2025) highlighted that Natural Language Processing (NLP) and Deep Learning techniques are increasingly being used to optimize customer relationships and improve banking efficiency. Temchenko (2025) further noted that AI-driven personalization, chat-bots, biometric onboarding, and voice-gesture banking significantly enhance customer interaction and user experience. Rahman et al., (2025) also observed that AI contributes toward improving customer experiences while simultaneously promoting a more practical and inclusive banking ecosystem.

14.2.2 Fraud Detection and Cyber Security

Another major theme identified in the literature is the application of AI in fraud detection and cyber security. Ahmed and Iqbal (2025) discussed how machine learning and deep learning models are increasingly used in detecting frauds and improving credit risk analysis compared to traditional systems. Salami et al., (2025) emphasized that AI-powered behavioural biometrics provide a next-generation solution for identifying complex fraudulent activities in digital banking systems. Onyshchenko et al., (2025) further analyzed AI-based fraud detection models and highlighted their effectiveness in strengthening financial transaction security and combating cyber threats across different countries. Temchenko (2025) also stressed that AI plays an essential role in anti-money laundering (AML), combating financing of terrorism (CFT), and fraud monitoring activities.

14.2.3 Credit Scoring and Lending Decisions

AI has also transformed credit scoring and lending decisions within the banking sector. Ahmed and Iqbal (2025) revealed that AI-based models are more effective than conventional credit scoring techniques in predicting defaults and assessing borrower risk. Shahid et al., (2025) noted that AI simplifies borrowing and lending processes by improving the efficiency and speed of credit assessment and transaction execution. Temchenko (2025) identified AI-enabled credit scoring as an important application area that improves decision-making accuracy and operational effectiveness. Meena et al., (2025) also highlighted the growing use of predictive modelling and AI-driven financial decision-making systems in banking and finance.

14.2.4 Risk Management and Bank Failure Prediction

A significant body of literature focuses on the role of AI in risk management and bank failure prediction. Kuanova et al., (2025) pointed out that AI-driven models improve financial risk governance and enable proactive, data-oriented decision-making. Lülök and Sebestyén (2025) found that unsupervised learning models are widely applied in bankruptcy prediction and risk analysis within the banking industry. Ahmed et al., (2025) examined AI-driven innovations in risk management and concluded that AI adoption enhances risk resilience and strengthens transaction security. Similarly, Aithal and Prabhu (2025) analyzed the evolution of the banking industry and highlighted the strategic importance of AI in improving banking operations and managing market challenges through analytical frameworks such as SWOC, ABCD, and PESTLE.

14.2.5 Operational Efficiency and Process Automation

Several researchers have discussed the contribution of AI toward improving operational efficiency and process automation. Singh et al., (2025) concluded that AI helps banking institutions optimize financial operations, reduce costs, and improve operational efficiency by automating routine activities. Temchenko (2025) explained that robotic process automation, workflow optimization, predictive maintenance, and automated document processing significantly improve productivity and reduce human error. Meena et al., (2025) also emphasized the role of AI in streamlining financial decision-making and operational management in banking institutions. Ahmed et al., (2025) additionally highlighted that AI adoption creates opportunities for reducing operational costs while improving service delivery and compliance accuracy.

14.2.6 Financial Inclusion and Accessibility

The literature also highlights AI's contribution toward promoting financial inclusion and accessibility. Ahmed and Iqbal (2025) observed that AI technologies support inclusive banking by improving access to financial services and enabling better credit assessment for underserved populations. Rahman et al., (2025) emphasized that AI helps create a more inclusive and sustainable global banking environment. Singh et al., (2025) similarly reported that AI enhances

financial inclusion through improved service accessibility and efficient banking operations. Temchenko (2025) further explained that AI-powered customer services and digital banking technologies make financial services more accessible to a wider population.

14.2.7 Regulatory Compliance and Ethical Governance

Another emerging theme in the literature is the role of AI in regulatory compliance and ethical governance. Sitnicka et al., (2025) examined the relationship between AI preparedness and banking sector profitability, highlighting the importance of ethics, governance, infrastructure, and institutional capabilities in achieving sustainable banking transformation. Aithal and Prabhu (2025) discussed the regulatory landscape surrounding AI adoption in banking and emphasized the need for strategic governance frameworks. Ahmed et al., (2025) stressed the importance of explainable AI systems, robust data governance, and regulatory harmonization to build stakeholder trust and ensure responsible AI implementation. Onyshchenko et al., (2025) also emphasized that ethical and secure AI implementation is essential for maintaining international banking standards and ensuring long-term sustainability in digital banking systems.

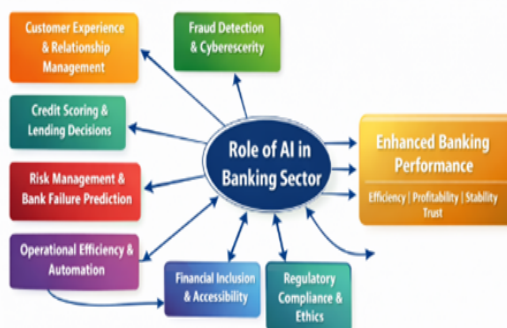


Figure 14.1: Role of AI in Banking Sector

14.3 Methodology

This study employs the systematic literature review (SLR) technique to examine existing academic research on the role of artificial intelligence in the banking sector. Relevant peer-reviewed journal articles and scholarly publications were systematically identified,

reviewed, and analysed to synthesize current knowledge on AI applications in banking. The SLR approach ensures methodological rigor, transparency, and reliability in consolidating prior research findings.

14.4 Analysis And Findings And Systematic Literature Review

Table 14.1: Systematic Literature Review.

Role of AI	References
Customer Experience and Relationship Management	(Abed et al., 2025); (Lülök and Sebestyén, 2025); (Temchenko, 2025); (Rahman et al., 2025)
Fraud Detection and Cybersecurity	(Ahmed and Iqbal, 2025); (Salami et al., 2025); (Onyshchenko et al., 2025); (Temchenko, 2025)
Credit Scoring and Lending Decisions	(Ahmed and Iqbal, 2025); (Shahid et al., 2025); (Temchenko, 2025); (Meena et al., 2025)
Risk Management and Bank Failure Prediction	(Kuanova et al., 2025); (Lülök and Sebestyén, 2025); (Ahmed et al., 2025); (Aithal and Prabhu, 2025)
Operational Efficiency and Process Automation	(Singh et al., 2025); (Temchenko, 2025); (Meena et al., 2025); (Ahmed et al., 2025)
Financial Inclusion and Accessibility	(Ahmed and Iqbal, 2025); (Rahman et al., 2025); (Singh et al., 2025); (Temchenko, 2025)
Regulatory Compliance	(Sitnicka et al., 2025); (Aithal and Prabhu, 2025); (Ahmed et al., 2025); (Onyshchenko et al., 2025)

The figure 14.1 highlights role of AI in banking sector.

14.5 Conclusion

The systematic literature review illustrates that artificial intelligence has a holistic and transformational role in the banking industry in various functional areas. The analyzed articles are always united by the fact that AI improves customer experience and

relationship management due to personalization and intelligent service delivery and contributes to the detection of fraud and cybersecurity at a high level, detecting intricate and changing patterns of threats. The analytics of credit scoring and lending based on AI contributes to more accurate and inclusive decisions and enhanced risk management systems will help predict the early failure of banks and enhance the stability of the institution. Moreover, the literature identifies that AI has helped in efficiency of operations and automation of processes through cost reduction, increased speed, and less human error. The review also highlights the importance of AI in enhancing financial inclusion through the augmentation of access to banking services and underserved population. Lastly, the capability to ensure regulatory adherence with the help of AI-monitored and controlled regulatory processes turns out to be an essential facilitator of viable and reliable banking practices. Altogether, the results verify that AI is a pivotal facilitator of efficiency, resilience, and innovation in the contemporary banking industry.

References

- [1] Abed, H., Zakariyah, H., et al. (2025). Usages of Artificial Intelligence in Forecasting and Strategic Analysis of Customer Needs in the Banking Sector. *International Journal of Academic Research in Accounting, Finance and Management Sciences*, 15(4), 120-137. <https://doi.org/10.6007/IJARAFMS/v15-i4/26789>
- [2] Ahmed, A., Shah, A., et al. (2025). AI-Driven Innovations in Modern Banking: From Secure Digital Transactions to Risk Management, Compliance Frameworks, and AI-Based ATM Forecasting Systems. *International Journal of Management Science Research*, 4 (3), 1145-1183.
- [3] Ahmed, F., and Iqbal, A. (2025). The role of artificial intelligence in enhancing credit risk management: A systematic literature review of international banking systems. *Pakistan Journal of Humanities and Social Sciences*, 13 (1), 478-492. <https://doi.org/10.52131/pjhss.2025.v13i1.2727>
- [4] Aithal, P. S., and Prabhu, V. V. (2025). The Evolution of Banking Industry in India: Past, Present, and Future with Special Emphasis on the Impact of AI on Banking Operations. *Poornaprajna International Journal of Teaching and Research Case Studies (PIJTRCS)*, 2 (1), 26-72. <https://doi.org/10.5281/zenodo.15050225>
- [5] Kuanova, L., Otegen, A., et al. (2025). Artificial intelligence-based risk management for the banking sector: Impact and challenges. *The*

Journal of Economic Research and Business Administration, 2(152), 35-51. <https://doi.org/10.26577/be202515223>

- [6] Lülök, G. and Sebestyén, Z. (2025). Latest Trends in the Use of Artificial Intelligence in the Banking Sector. *Financial and Economic Review*, 24 (2), 47-72. <https://doi.org/10.33893/FER.24.2.47>
- [7] Meena, R., Mishra, A. K., and Raut, R. K. (2025). Strategic insights: mapping the terrain of artificial intelligence (AI) in banking through mixed method approach. *VINE Journal of Information and Knowledge Management Systems*, 55 (5), 1192-1222. <https://doi.org/10.1108/VJIK-MS-01-2024-0028>
- [8] Onyshchenko, O., Ternovska, V., and Kovalov, V. (2025). Artificial Intelligence in Banking: Modern Models and Implementation Challenges. *Social Development: Economic and Legal Issues*, (12), 1-10. <https://doi.org/10.70651/3083-6018/2025.12.05>
- [9] Rahman, M. H., Raquiba, H., et al. (2025). AI Applications in Sustainable Banking: A Review of Applications, Challenges and Opportunities. *South Asian Research Journal of Business and Management*, 7 (6), 462-474. <https://doi.org/10.36346/sarjbm.2025.v07i06.001>
- [10] Salami, I., Popoola, A., et al. (2025). AI-powered behavioural biometrics for fraud detection in digital banking: A next-generation approach to financial cybersecurity. *Asian Journal of Research in Computer Science*, 18 (4), 473-494. <https://doi.org/10.9734/ajrcos/2025/v18i4632>
- [11] Shahid, S., Ahmed, S., et al. (2025). FinTech 4.0 and the Future of Global Finance: Blockchain, Artificial Intelligence, and Big Data as Catalysts of Digital Financial Innovation. *Inverge Journal of Social Sciences*, 4 (3), 364-379. <https://doi.org/10.63544/ijss.v4i3.173>
- [12] Singh, R., Mishra, R., et al. (2025). Applications of artificial intelligence for optimizing banking and financial operations: A systematic literature review and future research agenda. *Journal of Economic Surveys*, 39 (5), 2284-2302. 10.1111/joes.12693
- [13] Sitnicka, S., Mammadov, H., et al. (2025). Ethics, Institutions, Infrastructure, and Governance in AI National-Level Readiness: A Hidden Driver of Banking Transformation. *Business Ethics and Leadership*, 9 (3), 290-304. [https://doi.org/10.61093/bel.9\(3\).290-304.2025](https://doi.org/10.61093/bel.9(3).290-304.2025)
- [14] Temchenko, E. (2025). Artificial Intelligence in Banking: A Comprehensive Mapping Of Applications, Challenges, And Strategic Implications. *Socio-economic relations in the digital society*, 3(57), 5-18. <https://doi.org/10.55643/ser.3.57.2025.622>

Chapter 15

THE ADOPTION OF ARTIFICIAL INTELLIGENCE AND JOB REPLACEMENT: AN HUMAN RESOURCE MANAGEMENT PERSPECTIVE

Sukhvinder Kaur^{1,*} & Jasmeet Kaur²

¹Assistant Professor, Department of Commerce and Management, Khalsa Institute of Management and Technology for Women, Civil Lines, Ludhiana, Punjab, India- 141001.

²Assistant Professor, University School of Business (Commerce), Chandigarh University, Mohali, Punjab, India-140413.

*Email: sukhvinderkaurkimt@gmail.com

Abstract

Artificial Intelligence is consistently growing and gaining considerable standing in every field of economy. At the same time, users must decide which tools to use and implement them appropriately to execute the tasks at hand. However, the replacement of manpower by artificial intelligence is raising serious concerns in the job market. Job displacement is becoming a challenge for those who are performing repetitive and routine kinds of undertakings. Over dependence on artificial intelligence may reduce creativity, interpersonal skills and critical thinking of the employees but its speed, reduced operational cost and error-free work make organizations competitive and productive. Despite the threats it's the need of the hour to upgrade the manpower inventory by reskilling and up skilling the manpower available so that they can become technically sensible as artificial intelligence is restructuring the future of work. The organizations can maintain a balance between the technology and manpower as it brings undeniable advantages. The chapter will elaborate how artificial intelligence

is replacing jobs and which positions and work profiles are getting affected by adopting artificial intelligence. The chapter also aims to explore the benefits of using artificial intelligence in different job positions. The key human resource management challenges and opportunities due to the use of artificial intelligence are also covered in this chapter.

Keywords: Employees, Human Resources, Jobs, Replacement, Management

15.1 Introduction

AI has emerged as a new force and has entered numerous industries changing how people work, live, and interact. Its influence is immensely beyond and has real-life applications in the fields of healthcare and banking as well as in the manufacturing and entertainment world. Artificial Intelligence (AI) assists organizations in raising the operational effectiveness and promptly informed choices, as well as develops products and services (Vishwanath and Vaddepalli, 2023). The effect of AI on Human Resources (HR) is one of the most well-informed and encouraging of such disciplines. In the face of the expected changes in industries due to artificial intelligence (AI) and automation, the issue of technological unemployment is growing (Oman et al., 2025). However, certain problems must be addressed to make sure that the use of AI in HRM is justified and efficient; the problems consist of; ethics (Weng and Nanda, 2024) algorithms, data privacy (Weng and Nanda, 2024), and reskilling of the workforce (Xavier et al., 2025). The implementation of AI in human resource management requires changing the competency required by the human resource department, encompassing digital skills, data skills, and strategic mentality, as well (Jetha et al., 2021). Introducing AI into the paradigm enables HR departments to shift to strategic roles rather than administrative ones to increase organizational efficiency, productivity, and employee experiences (Suresh and Shanmugapriya, 2024). With industry discovering the aids of these technologies, automation and AI are becoming a necessity in such aspects as recruiting manpower, talent management, performance reviews, and engaging employees. Machine learning and AI tools have the ability to analyse large volumes of data, which offer useful insights that help the HR to make decisions, anticipated talents need, and

forecast potential retention issues. Moreover, automation simplifies HR functions, which gives more saliency to strategic planning, staff growth, and innovation. Flexible AI-based applicant tracking systems (ATS) have the ability to filter through thousands of resumes in a few seconds and identify the most suitable applicants according to established criteria (e.g., skills, experience, cultural fit, etc.). Natural language processing (NLP) chatbots can help with the initial communicative engagement with candidates, queries, scheduling interviews, and even preliminary assessment (Kirankumar, 2021). Even the International Monetary Fund (IMF 2024) in its report emphasized the fact that AI will impact 40 percent of global jobs, and voluminous jobs are to be substituted. Even though AI is a productivity boost, particularly in terms of automation and services, it also removes jobs in tedious and monotonous activities, e.g., data entry and assembly line work (Ilmarset al., 2019; Sonderling et al., 2022; Georgieff and Hyee 2021). Both blue-collar and white-collar jobs are being affected by the emergence of Artificial Intelligence (AI), but the difference lies in the type and degree of impact is dramatic between the two (Harsha, 2025). The World employment and social outlook report by The International Labour Organization, 2024 points out that about 85 million jobs can be replaced with automation in the industries by 2030 with manufacturing experiencing the most severe challenges. Nonetheless, this forecast is in parallel with facts according to which AI will provide new types of jobs that will completely transform labour demand and not necessarily decrease it (Damioli et al., 2024). Nevertheless, even with the significant opportunities offered by highly developed technologies in HRM, employees can perform a variety of tasks that cannot be executed by machines (Agrawal et al., 2017; Maedche et al., 2019).

Artificial intelligence will cease to be an experimental feature very soon but will become essential infrastructure of organizations, with the impacts being experienced on most of the job descriptions. In this chapter, the author conducts an in-depth discussion of the complexity of AI on employment, touching upon 3 problematic aspects: job displacement trends, sector benefits, and human resources management issues. Although between 2025 alone some 200,000 to 300,000 U.S. jobs are expected to be displaced or foregone, which is 0.13-0.20% of the workforce, the effect is not uniformly spread out (J.P. Morgan Research Report, 2026). Clerical women are

at a disproportionate risk with 86 percent of the vulnerable labor force in office jobs being women (Times of India, 2026). The given phenomenon is not a new one; there were examples of it in the past (such as the Industrial Revolution) when manual labor was automated, creating new careers. However, AI is a wider concept, as it penetrates the mental activity through neural networks and machine learning. It has been reported that there are 300 million full-time jobs in the world that may be impacted, and the most susceptible to it are routine positions in data entry, assembly, and simple analysis (Sachs, 2023). In developed economies, it is exposed to 60, which further increases inequality by playing on the low-skilled workers (Sachs, 2023). On the other hand, AI adoption has contributed to productivity increase through automation of routine jobs especially in healthcare, finance, and manufacturing. The chapter also discusses to identify major human resource management challenges and opportunities as a result of using artificial intelligence. It can be implied that AI is an important source of displacement to certain groups of people and certain lines of work, yet it can become the means of economic expansion, assuming that the effective policy frames and flexible human resource policies are introduced. Companies cannot but revise manpower inventory via reskilling and thus creating technical sensibility during restructuring. In order to conduct this study qualitative review has been undertaken, based upon peer-reviewed journals, reports (IMF, Goldman Sachs), and various industry analyses reports. There has not been any primary data collection, and the chapter focuses on thematic review according to the aims of the abstract.

15.2 Research Design

The research design of this study follows a desk-based and non-empirical study in nature. Instead of gathering primary data (e.g., surveys, interviews, or experiments), the research analyzes the existing literature to critically review the existing knowledge on the topic of artificial intelligence (AI) and Job markets. The focus of the research is to bring together and organize existing theoretical frameworks, empirical research, and policy discussions and not to produce new data on the field; hence a desk-based approach is followed. This structure enables covering all recent advances in

AI and labour research, especially since the fast development of AI technologies since 2019.

15.3 Literature Review

The discussion on technology and employment is not new, as it began with the industrial revolution. Nevertheless, the scholarly analysis of the particular effect of AI is a particular and swiftly developing field of study. The initial literature on automation was mainly concerned with replacement of workforce with capital on monotonous manual work. The seminal work of Autor, Levy and Murnane (2003) established the Routine-Biased Technological Change hypothesis. This framework posits that while technology displaces routine labor through automation, it simultaneously complements non-routine cognitive and manual tasks. This paradigm provides a robust explanation for the labor market polarization observed throughout the late 20th and early 21st centuries.

With the development of AI technologies, the methodology of research had to develop to reflect the expanded options. The probabilistic study of occupational vulnerability to computerization by Frey and Osborne (2013) is a crucial step. Their projection that 47 percent of all US jobs could be automated led to a heated discussion and occasioned further studies. Although their approach was novel, later writers have criticized their use of a broad occupational approach, and have proposed a more task-oriented analysis. The latter change can be traced in the studies by Acemoglu and Restrepo (2018) who highlighted that automation influences specific tasks in the jobs but not the occupations, which makes it possible to distinguish between the impact of automation on the displacement and reinstatement effects.

More recent works have been dedicated to the distinct features of modern AI and especially machine learning and generative AI. The AIOE measure proposed by Felten et al., 2018 and the SML rubric proposed by Brynjolfsson et al., 2018 can be seen as important methodological improvements. The frameworks transcend the basic routine/non-routine dichotomy to evaluate the particular AI capabilities, e.g. pattern recognition and content generation. They point out that high-paid, and highly-educated professionals tend to

be more exposed to AI than low-paid service workers, which is an inversion of the RBTC hypothesis.

With the advent of generative AI, impact models have had to be re-evaluated again. Creative and analytical tasks Starting in 2023, with Eloundou et al., and recent working papers as of 2024-2025 (e.g., at Stanford and Brookings) have begun to quantify the exposure of creative and analytical tasks to Large Language Models (LLMs). This new body of literature finds a threat to jobs that were once thought safe to automation, namely, software coding, writing, and legal analysis, which is termed a generative AI exposure. Nevertheless, there is still a substantial distance between relating these exposure indicators to achieved job displacement and the definite adaptive capabilities of the workforce.

15.4 AI-Loss of Jobs: Analysis And Affected Jobs

15.4.1 The Present Situation Regarding Job Displacement is as follows

It is remarkable that according to Challenger, Gray and Christmas, the figures estimated to lose jobs specifically to AI in 2024 are approximately 12,700 jobs, often targeting entry-level roles or customer service in U.S. and since pilot programs became implemented, these numbers have risen exponentially. 14 percent of the workforce is displaced, which indeed includes job termination (McKinsey Report, 2018).

But dramatic restructuring of roles in which the major tasks were automated and there was a need to change or transfer roles. The effect is also largely skewed towards the younger generation of people compared to the past automation waves. Occupations with high levels of exposure to AI, especially young and middle-aged employees between 22 and 25, have suffered a loss in employment of 6-13% (Erik et al., 2025). This hollowing out of the entry-level positions, which will eventually make up the senior professionals later, is especially visible in the field of technology and creativity. Firms are also adopting AI to do the first drafting, coding, and data analysis work that they would have given to their junior employees that further increases the entry barrier of new graduates.

15.4.2 Majority of the Vulnerable Occupations and Positions

The susceptibility to the replacement of AI is not equally distributed. It is a heavy concentration between routine mental jobs and high cost of labor. In a study conducted on U.S. workforce it was determined that a high-risk group of 6.1 million workers is deemed to be at the risk of a high AI exposure and low adaptive capacity, the so-called double jeopardy (Manning et al., 2026).

Administrative and Clerical positions: This group is the epicenter of displacement present. The administrative support jobs include tasks that can be scheduled, data entered, letters written, records kept, which are exactly in line with the capabilities of generative AI agents.

Office Clerks: There are about 2.5 million high-risk workers at general offices. In case of secretaries and administrative assistants, 1.7 million jobs are susceptible to automated schedules and communication devices (International Labour Organization, 2016).

Customer Service Representatives: Chatbots and voice AI agents are quickly taking over the support positions. Recent research on service employees, particularly customer service front-line staff provides strong evidence that the integration of intelligent bots and automation technologies (such as voice recognition assistants, chatbots and other AI-driven service systems) is increasingly being used to streamline processes and enhance task efficiency. (Henkel et al., 2020; Li et al., 2019; Prentice et al., 2020).

Gender Impact: This form of displacement has a strong gender aspect; 86% of those in these high-vulnerability clerical jobs are women, a factor that has concerned the increasing gender economic inequalities (ILO, Times of India, Economic Times Report). 29% of female-dominated professions are exposed to Generative AI, while only 16% of male-dominated occupations face the same level of exposure (ILO 2026 Report). There is an international trend toward female domination in the HR occupation. (Scarborough, 2017; Cappelli et al., 2019)

White-collar and Professional Roles: The robotics revolution that struck manufacturing is being pointed at the knowledge worker, which the AI revolution is doing directly. AI has specific impact on white-collar workforce automation of tasks in professional fields like

Law, Finance, Customer Support, and Journalism (Sathyanarayana and Harsha 2025).

Software Developers / Software Award Engineers: Senior architects are still in demand; however junior coders are being affected by AI-based code generators (e.g. GitHub Copilot) that can create boilerplate code on the fly.

Financial Analysts: The positions characterized by regular financial reporting and simple data analysis are being automated. In finance, AI-powered algorithms manage high-frequency trading, fraud detection, credit scoring, and risk assessment with high precision. Robo-advisors such as Betterment and Wealth front automate investment portfolio management based on client preferences and risk profiles (Arner et al., 2016).

Legal Professionals: With AI tools capable of searching contracts and case law at a faster rate than a human, legal research assistants and paralegals are being displaced. In the legal sector, AI tools like ROSS Intelligence and LexisNexis use NLP to automate legal research, contract analysis, and case prediction, thereby significantly reducing the time and cost associated with legal due diligence (Surden, 2014; Remus and Levy, 2017).

Content Writers: LLM is automating the work of copywriters, technical writers and translators and can create text of human quality. In journalism, automation tools such as Wordsmith (by Automated Insights) and Quill (by Narrative Science) are used to generate news stories, financial reports, and sports summaries from structured data inputs. AI is also applied in content recommendation, fact-checking, and audience analytics, helping newsrooms optimize distribution and personalize content (Carlson, 2015; Dorr, 2016).

15.4.3 Sectors that AI Displacement will Impact the Most

The table 15.1 given below provides overview of sectoral analysis of the impact of AI displacement.

15.4.4 Adaptive Capacity Analysis of Workers

To explain displacement, one needs to examine not only exposure, but resilience. High adaptive capacity is in highly exposed AI-workers. They tend to be individuals with cross-functional skills, access to

Table 15.1: Sectoral Analysis of the impact of AI Displacement.

Sector	Primary Displaced Functions	AI Technology Driver
Information Technology	Coding, testing, system administration, helpdesk support	Generative code assistants, automated monitoring agents
Medical	Medical transcription, billing/coding, diagnostic pre-screening	Speech-to-text AI, computer vision, predictive analytics
Finance and Insurance	Underwriting, claims processing, fraud detection, data entry	Algorithmic assessment of risk, document processing AI
Media/Entertainment	Video editing, sound engineering, basic journalism, translation	Generative video/audio tools, LLMs
Manufacturing	Quality inspection, inventory management, machine control	Computer vision, machine predictive maintenance AI, robotics

Source: Authors Compilation

financial cushions and excellent educational qualifications (e.g., top managers, highly specialized physicians) that can use AI to enhance their productivity instead of losing their jobs. But many may not have a structural path to adaptation. Some of the factors affecting low adaptive capacity include:

Age: Employees near to their retirement are more vulnerable in displaced jobs and find it difficult to be reemployed. For older individuals, job stability becomes increasingly important as they are near retirement, and they may be less inclined to pursue new opportunities or acquire new skills. (Liu et al., 2023; Aisa and Cabeza, 2025)

Geographic Isolation: The vulnerable workers are highly clumped around smaller metropolises and state capitals where administrative employment is a major economic activity.

Skill Specialization: Employees who have limited skills (e.g., manual data entry professionals) have a more difficult time making

a pivot than those with general and transferable skills. The rapid advancement of AI has widened the skills gap, leaving many individuals unprepared to meet the demands of emerging technologies (Case, 2024).

15.5 Artificial Intelligence Perks In The Workplace

In as much as displacement is a major issue, the big picture economic story of AI is that of increased productivity and value generation. To most of the working population, AI is not a cause, but rather a force multiplier.

15.5.1 Productivity Enhancement

The data that has been aggregated based on the initial adopters indicate that the workforce that used the generative AI tools saved an average of 5.4% of work hours per week (Bick et al., 2025). Through automation of low-value and routine tasks, including the summation of meetings, creation of email templates, and data cleaning, AI also frees human workers to concentrate on high-value work, such as strategic planning, progressive solutions, and relationship construction. Moreover, AI improves the quality of decision making because it can analyze large volumes of data and find patterns and insights that do not exist in the human reasoning process and results in better and quicker business results.

15.5.2 Sector-Specific Benefits

Healthcare: The AI in the healthcare sector is a lifesaving device that counteracts the life-threatening shortages of labor.

Diagnostic Support: AI algorithms analyze the MRI and CT scans with very high precision that is usually higher than that of a human expert, and indicate abnormalities that should be tested by a radiologist and decrease the number of errors during the diagnostic process.

Administrative Relief: Automated documentation tools hear the visits of patients and write clinical notes, which directly targets the most significant factor of burnout in physicians, paperwork.

Personalized Medicine: AI uses genetic and clinical data to personalize the treatment plan of oncology and chronic diseases, enhancing patient outcomes.

Financial Services: AI is used in the finance sector to increase the efficiency and security.

Fraud Detection: Real-time AI algorithms apply transactional patterns to identify fraud and block it immediately, saving billions of assets.

Risk Assessment: Sophisticated algorithms will enable more advanced credit scoring, which may lead to improved access to credit to underserved groups since it will take into account a broader range of factors than a classic FICO score.

Market Analysis: AI machines analyze all news and market data around the world to predict trends and help in smarter investment strategies.

Manufacturing: The driver of the smart factory is AI.

Predictive Maintenance: IoT sensors in conjunction with AI anticipate machine downturns even before it happens, thus saving a huge amount of money on downtime.

Generative Design: AI is utilized by engineers to peruse thousands of possible designs of parts in a way that minimizes weight and maximizes strength in ways that cannot be identified by human designers.

Safety: The computer vision systems are used in factories and take safety hazards into consideration as well as the observance of protocols.

Education: AI has the hope of education democratization. Individual Learning: AI tutors will dynamically change the difficulty of the curriculum based on student performance, so that there is no student left behind or bored.

Automated Grading: Artificial intelligence can be used to mark tests and offer immediate feedback, so teachers have more time to conduct mentorship and teaching.

15.5.3 AI Augmentation vs. Replacement

The perceived dichotomy between labor replacement and retention is largely a myth; the empirical reality is one of augmentation. Successful implementation models demonstrate that AI functions as a 'copilot,' where human agency remains central to the process. In the legal sector, while AI streamlines case law research, the overarching strategy remains the domain of human practitioners. Similarly, in medicine, AI assists in diagnostic precision, yet the clinical treatment plan and subsequent ethical deliberations necessitate human intervention. This human-in-the-loop framework leverages AI for its computational capacity while relying on human professionals to provide nuance, ethical oversight, and empathy.

15.6 Human Resource Management: Problems And Potentiality

Human Resource (HR) departments being the gatekeepers of the workforce are on the frontline of the AI transition. They are confronted with a paradox, namely the need to use AI to increase the efficiency of HR, but, at the same time, address the ethical and human risks of its implementation that are so profound.

15.6.1 Recruitment and Hiring Problems

AI has transformed the recruitment process, yet it has also brought with it malevolent types of discrimination.

Algorithmic Bias: Recruitment algorithms are based on past data, so they tend to recreate previous biases. As an example, it has been discovered that systems punish resumes that include the word women can be punished (e.g., women can be chess club). On the other hand, there are models that are also biased towards black male applicants because of the skewed training data. Algorithmic bias is one of the frequent problems in AI-based recruitment (Mujtaba and Mahapatra, 2025).

Risks of Automated Screening: Screening systems purporting to assess the personality of candidates based on facial micro-expressions have been massively criticized as pseudoscience and discriminatory against applicants with neuro divergent personalities or non-English

speakers. Lack of human consideration in AI is challenging for organizations (Mazarakis et al., 2023).

The Dehumanization of the Candidate Experience: Excessive automation has significantly eroded candidate satisfaction and adversely impacted job-seeker mental health (Khogali and Mekid, 2023). A primary driver of this trend is the 'Black Box' rejection—a phenomenon where applicants receive near-instantaneous, automated denials devoid of qualitative feedback. This lack of transparency fosters a sense of procedural injustice, as candidates perceive their professional potential is being dismissed by an impersonal algorithm rather than being evaluated by a qualified practitioner.

15.6.2 Algorithmic Management and Surveillance at the Workplace

A significant ethical problem is the emergence of the so-called bossware or algorithmic management tools. Artificial intelligence has become able to monitor screen time and keystroke, and even screen tones of voice on a customer care call. Although this may maximize productivity, it will suggest the emergence of a so-called digital panopticon that undermines trust and promotes stress and diminishes employee autonomy. HR leaders need to successfully walk the tightrope of ensuring there is no conflict between performance management and invasive surveillance, by ensuring that there is well defined governance on how data is gathered and utilized.

15.6.3 HR Opportunities of AI Adoption

Nonetheless, AI has revolutionary capabilities to the HR process.

Operational Efficiency: The HR organizations using AI note efficiency improvements. Daily routine employee inquiries in the form of benefits and payroll are currently being addressed by chatbots, leaving HR personnel with the ability to focus on strategic aspects. With the growing adoption of AI in recruitment, data-driven evaluations simplify and accelerate candidate assessment, by providing a more efficient and precise alternative to conventional approaches. (Howard, 2019; Weng and Nanda, 2024).

Talent Intelligence: AI solutions have the capability to compare the skills portfolio of an organization overall, including gaps and

internal mobility opportunities that might be overlooked by human managers. This data-driven strategy enhances retention through a perfect match of employees and growth prospects. AI technology can be used to reduce bias in hiring, provided it is used prudently. AI algorithms can analyze applicants on objective grounds and not on individual features (Oman et al., 2024; Ncube et al., 2025).

Strategic Workforce Planning: Predictive analytics can help HR predict the risk of attrition as well as future talent demands, moving the department toward the proactive instead of the reactive. HR department can devote their time to strategic planning (Ncube et al., 2025; Benabou and Touhami 2025).

15.6.4 Compliance and Ethical Dilemmas

Privacy of information has to be maintained by firms using AI. The most important is adherence to the changing rules such as EU AI Act and EEOC regulations. HR should make transparency, which is letting the employees know whether AI is used to assess them or not. Moreover, accountability systems also need to be put in place, when an AI decides to hire or to fire a person; there must be a human being in charge of such decision.

15.7 Future of Work: In The Age of AI, Skills And Reskilling

15.7.1 Re-Engineering Skills

World Economic Forum estimates that 40 percent of the core job skills will be modified by 2030. The shelf-life of technical skills is reducing whereas, the value of human skills is increasing.

AI Literacy: Simple skills in communication with AI (prompt engineering, AI ethics) are emerging as a basic skill like computer literacy.

Soft Skills Renaissance: Skills that AI cannot readily duplicate such as empathy, complex negotiation, creative ideation, and strategic leadership are becoming the key distinguishing factors of human talent.

15.7.2 Upskilling and Reskilling Programmes

The scale of displacement leads to the need of a “Marshall Plan” of reskilling. Corporate training programs are moving away with the fixed course library towards their AI personalized learning experience platform (LXP). Nevertheless, the individual attempts are not enough. There is a rise in public-private partnerships to update vocational training, which makes sure that workers who lost their jobs in the shrinking sectors (e.g., administrative support) are retrained in the expanding ones (e.g. green energy, healthcare, AI maintenance).

15.7.3 Sector-Specific Labor Shortages and AI

Remarkably, the association between AI impact and sector vacancy rates is strongly positive. The industries that are most aggressively embracing AI, such as healthcare and IT, tend to be the ones that have the most intense labor shortages. In this regard, AI is not a job killer but rather a needed survival tool. To illustrate, the US is projected to be short of nursing professionals; administrative automation through AI is the only solution available to ensure the care standards are not compromised with the impossibility of tripling the number of human heads.

15.8 Implications And Recommendations

15.8.1 For Policymakers

Governments cannot start being bystanders. The most at-risk group of women in clerical positions requires specific assistance since they are at risk of displacement most of all. Tax incentives on corporate reskilling investments and contemporary social safety nets should be introduced to help the workers through policy interventions. Moreover, the discriminatory algorithm in hiring and management should be successfully regulated.

15.8.2 For Organizations

Leaders need to take a human-centric approach to AI. The whole implementation process should be transparent and the employees should also be included in the process of automation of their working process. The efficiency benefits of AI could be used by organizations

to reinvest in the up-skilling of their employees in a cycle of loyalty and productivity. Board of ethics AI to be employed in governing the risks of deployment should be set up.

15.8.3 For Workers

Gone are the days of the job for life; the days of learning for life are here. Employees should develop flexibility on their part. These include not avoiding AI tools and developing a T-shaped skill profile with profound knowledge of one area and general knowledge of digital tools, paying attention to the interpersonal dimension of their jobs that cannot be totally automated.

15.8.4 Conclusion

Artificial Intelligence is a two-sided sword that has the power to both remove and promote the workforce. Displacement is a reality and a serious one, that it affects lives of hundreds of thousands of people and that it disproportionately affects certain demographics. However, the statistics do not confirm the story of the inevitable mass unemployment. Rather, intricate shifts in which roles are un-bundled, tasks are automated and new types of value creation are created.

The future of work is not going to be determined by the abilities of the machines, but the efficiency of human cooperation with them. The HR management challenges, prejudice, lack of skills; all of them are deep and can be resolved through deliberate leadership and ethical practices. Society can take on the risks associated with the vulnerable groups and vigorously seek the productivity gains of augmentation by recognizing the dangers of augmentation. The opportunity to re-design work to be less routine and more human that AI revolution promises is almost unprecedented in the history of work, given the general will to cope with the transition to AI and keep humans in the center of the transition plans.

References

- [1] Acemoglu, D., and Restrepo, P. (2018). The Race Between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. *American Economic Review*, 108(6), 1488-1542. <https://doi.org/10.1257/aer.20160696>

- [2] Agrawal, A., Gans, J., and Goldfarb, A. (2017). What to expect from artificial intelligence? *MIT Sloan Management Review*, 58(3), 23-26. <http://mitsmr.com/2jZdf1Y>
- [3] Aísa, R., and Cabeza, J. (2025). Artificial intelligence: Redefining the retirement pattern. *Research in Economics*, 79. <https://doi.org/10.1016/j.rie.2025.101062>
- [4] Arner, D. W., Barberis, J. N., and Buckley, R. P. (2016). The evolution of Fintech: A new post-crisis paradigm? *Georgetown Journal of International Law*, 47, 1271–1319. <https://dx.doi.org/10.2139/ssrn.2676553>
- [5] Autor, D., Levy, F., and Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics*, 118(4), 1279-1333.
- [6] Benabou, A., and Touhami, F. (2025). Artificial intelligence in Human Resource Management: A PRISMA-based Systematic review. *Acta Informatica Pragensia*, 14(3), 489-505. <https://doi.org/10.18267/j.aip.264>
- [7] Bick, A., Blandin, A., and Deming, D. J. (2025). The Rapid Adoption of Generative AI. *National Bureau of Economic Research Working Paper No. 32966*. <http://www.nber.org/papers/w32966>.
- [8] Brynjolfsson, E., Chandar, B., and Chen, R. (2025). Canaries in the Coal Mine? Six Facts about the Recent Employment Effects of Artificial Intelligence. *Stanford Digital Economy Lab*.
- [9] Brynjolfsson, E., Mitchell, T., and Rock, D. (2018). What Can Machines Learn and What Does It Mean for Occupations and the Economy? *AEA Papers and Proceedings*, 108, 43-47. <https://doi.org/10.1257/pandp.20181019>Top of Form
- [10] Cappelli, P., Tambe, P., and Yakubovich, V. (2019). Artificial intelligence in human resources management: challenges and a path forward. *SSRN Electronic Journal*, <https://doi.org/10.2139/ssrn.3263878>
- [11] Carlson, M. (2015). The robotic reporter: Automated journalism and the redefinition of labor, compositional forms, and journalistic authority. *Digital Journalism*, 3(3), 416–431. <https://doi.org/10.1080/21670811.2014.976412>
- [12] Case, T. (2024). AI skills gap widens: Employers embrace AI, but employees left behind. *WorkLife*. <https://www.worklife.news/technology/ai-skills-gap-widens-employers-embrace-ai-but-employees-left-behind/>
- [13] Challenger, Gray and Christmas. (2024). AI Employment Impact Report 2024. Chicago, IL.
- [14] Damioli G., Roy, V. V., Vertesy, D., Vivarelli, M. (2024). Drivers of employment dynamics of AI innovators. *Technological Forecasting and Social Change*, 201, 123249. <https://doi.org/10.1016/j.techfore.2024.123249>

- [15] Dorr, K. N. (2016). Mapping the field of algorithmic journalism. *Digital Journalism*, 4(6), 700–722. <https://doi.org/10.1080/21670811.2015.1096748>
- [16] Eloundou, T., Manning, S., Mishkin, P., and Rock, D. (2023). GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models. *OpenAI Working Paper*.
- [17] Felten, E. W., Raj, M., and Seamans, R. (2018). A Method to Link Advances in Artificial
- [18] Frey, C. B., and Osborne, M. A. (2017). The Future of Employment: How Susceptible Are Jobs to Computerisation? *Technological Forecasting and Social Change*, 114, 254–280. <https://doi.org/10.1016/j.techfore.2016.08.019>
- [19] Gen AI, occupational segregation and gender equality in the world of work (2026). *International Labour Organization Report*.
- [20] Georgieff, A., and Hye, R. (2021). Artificial intelligence and employment: New cross-country evidence. *OECD Social, Employment and Migration Working Papers*. ISSN: 1815-199X (Online). <https://doi.org/10.1787/1815199X>
- [21] Henkel, A. P., Bromuri, S., Iren, D., and Urovi, V. (2020). Half human, half machine augmenting service employees with AI for interpersonal emotion regulation. *Journal of Service Management*, 31(2), 247–5818. <https://doi.org/10.1108/JOSM-05-2019-0160>
- [22] Howard, J. (2019). Artificial intelligence: Implications for the future of work. *American Journal of Industrial Medicine*, 62(11), 917–926. <https://doi.org/10.1002/ajim.23037>
- [23] Ilmars, U et al. (2019). Artificial intelligence in workplaces and how it will affect employment in Latvia. *Environment Technology Resources Proceedings of the International Scientific and Practical Intelligence to Occupational Abilities*. *AEA Papers and Proceedings*, 108, 54–57. ISSN 2574-0768
- [24] J.P. Morgan, "Why AI might strain the economy before it booms" (February 23, 2026).
- [25] Jetha, A., Shamaee, A., Bonaccio, S., Gignac, M. A., Tucker, L. B., Tompa, E., and Smith, P. M. (2021). Fragmentation in the future of work: A horizon scan examining the impact of the changing nature of work on workers experiencing vulnerability. *American Journal of Industrial Medicine*, 64(8), 649–666. <https://onlinelibrary.wiley.com/doi/pdfdirect/10.1002/ajim.23262>
- [26] Khogali, H. O., and Mekid, S. (2023). The blended future of automation and AI: examining some long-term societal and ethical impact features. *Technology in Society*, 73, 102232. <https://doi.org/10.1016/j.techsoc.2023.102232>

- [27] Kirankumar, R. (2021). The Future of Work: How AI and Automation Are Reshaping Human Resource Management. *International Journal of Advanced Research*, 8(3).
- [28] Li, J. J., Bonn, M. A., and Ye, B. H. (2019). Hotel employee's artificial intelligence and robotics awareness and its impact on turnover intention: The moderating roles of perceived organisational support and competitive psychological climate. *Tourism Management*, 73, 172–181. <https://doi.org/10.1016/j.tourman.2019.02.006>
- [29] Liu, Y., Meng, X., Li, A. (2023) AI's Ethical Implications: Job Displacement. *Advances in Computer and Communication*, 4(3), 138-142. <https://doi.org/10.26855/acc.2023.06.006>
- [30] Maedche, A., Legner, C., Benlian, A., Berger, B., Gimpel, H., Hess, T., Hinz, O., Morana, S., and Söllner, M. (2019). AI-based digital assistants. *Business and Information Systems Engineering*, 61(4), 535–544. <https://doi.org/10.1007/s12599-019-00600-8>
- [31] Manning, S., Aguirre, T., Muro, M., and Methkuppally, S. (2026). Measuring US Workers Capacity to Adapt to Ai Driven Job Displacement. *National Bureau of Economic Research*, working paper.
- [32] Mazarakis, A., Bernhard-Skala, C., Braun, M., and Peters, I. (2023). What is critical for human-centered AI at work? -towards an interdisciplinary theory. *Frontiers in Artificial Intelligence*, 6, 1257057. <https://doi.org/10.3389/frai.2023.1257057>
- [33] McKinsey Global Institute (2017/2018) report, "Jobs lost, jobs gained: Workforce transitions in a time of automation,"
- [34] Mujtaba, D. F., and Mahapatra, N. R. (2025). Fairness in AI-Driven Recruitment: Challenges, metrics, methods, and future directions. <https://doi.org/10.48550/arXiv.2405.19699>
- [35] Ncube, T. R., Sishi, K. K., and Skinner, J. P. (2025). The impact of artificial intelligence on human resource management practices: An investigation. *SA Journal of Human Resource Management*, 23. <https://doi.org/10.4102/sajhrm.v23i0.2960>
- [36] Nigar, M., Juli, J. F., Hossain, M. K., Golder, U., and Alam, M. J. (2025). Artificial intelligence and technological unemployment: Understanding trends, technology's adverse roles, and current mitigation guidelines. *Journal of Open Innovation: Technology, Market, and Complexity*. <https://doi.org/10.1016/j.joitmc.2025.100607>
- [37] Oman, N. Z. U., Siddiqua, N. A., and Noorain, N. R. (2024). Artificial Intelligence and its ability to reduce recruitment bias. *World Journal of Advanced Research and Reviews*, 24(1), 551–564. <https://doi.org/10.30574/wjarr.2024.24.1.3054>
- [38] Peiwen, C., Sulaiman, N., Zhenglong, S. (2025). The Impact of Artificial Intelligence Application on Job Displacement and Creation:

A Systematic Review. *International Journal of Research and Innovation in Social Science*. <https://doi.org/10.47772/IJRISS>

- [39] Prentice, C., Dominique Lopes, S., and Wang, X. (2020). Emotional intelligence or artificial intelligence—an employee perspective. *Journal of Hospitality Marketing and Management*, 29(4), 377–403. <https://doi.org/10.1080/19368623.2019.1647124>
- [40] Remus, D., and Levy, F. (2017). Can robots be lawyers? Computers, lawyers, and the practice of law. *George town Journal of Legal Ethics*, 30(3), 501–558.
- [41] Sachs, G. (March 2023). "The Potentially Large Effects of Artificial Intelligence on Economic Growth" (authored by economists Joseph Briggs and Devesh Kodnani).
- [42] Sathyanarayana, S., and Harsha, H. (2025). Navigating the Future of Work: The Impact of Artificial Intelligence on Jobs, Skills, and Workforce Dynamics. *International Journal of Business and Management Invention (IJBMI)*, 14(5), 67-79.
- [43] Scarborough, W. J. (2017). The [human resource management] revolution will not be televised: the rise and feminization of human Resource Management and labor Force equity. *Social Currents*, 4(5), 448–461. <https://doi.org/10.1177/2329496517704871>
- [44] Surden, H. (2014). Machine learning and law. *Washington Law Review*, 89(1), 87–115.
- [45] Suresh, R., and Shanmugapriya, S. (2024). Revolutionizing human resource management: The future of HR with artificial intelligence and automation. *International Journal of Research in Human Resource Management*, 6(2): 419-423 DOI: <https://doi.org/10.33545/26633213.2024.v6.i2e.245>
- [46] Vishwanath, B., and Vaddepalli, S. (2023). The Future of Work: Implications of Artificial Intelligence on HR Practices. *Journal of Propulsion Technology*, 44(3).
- [47] Weng, Y., and Nanda, A. (2024). The Future of Work: AI and Automation in Human Resource Operations and Employee Experience. *Nanotechnology Perceptions*, 20(7), 61–71,
- [48] Xavier, N., Mishra, B. S., Dokku, S. R., Kumar, T. Ch. A., Singh, S. K., and Vyas, B. (2025) The Future of Work: How AI and Automation Are Transforming HR Practices. *Advances in Consumer Research*, 2 (2), 813-821.

[illegible]

How to cite

Any chapter of this book should be cited as:

Author, A. A. (2026). Title of the cited chapter. In Dr. Aanchal Arora, et al. (Ed.), Artificial Intelligence: Multidisciplinary Stance and Applications. (pp. 1xx–1xx). Vyom Hans Publications. ISBN (E): 978-81-686211-3-8; ISBN (P): 978-81-686211-2-1

All chapters of this book published under the CC-BY license at <https://press.vyomhansjournals.com> under Vyom Hans Publications.

Book is available online at <https://press.vyomhansjournals.com>; Amazon and Flipkart marketplaces.