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Foundation Models Beyond Generative AI: Emerging Applications Across Science, Industry and Public Services

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Abstract

Foundation models have emerged as a major development in Artificial Intelligence, initially gaining widespread attention through generative applications such as conversational systems, image generation, code generation, and multimodal content creation. However, the significance of foundation models extends well beyond conventional generative AI. Their ability to learn broad representations from large and diverse datasets creates opportunities for scientific discovery, industrial optimisation, healthcare, climate modelling, infrastructure management, public administration, and decision-support systems. Increasingly, foundation models are being developed for domains involving scientific measurements, biological sequences, remote sensing, time-series data, industrial processes, and multimodal information rather than only human-generated text and images.

This study examines emerging applications of foundation models beyond generative AI across science, industry, and public services. A qualitative and descriptive research methodology based on secondary academic literature, technical publications, institutional reports, and policy documents is adopted. The study explores scientific foundation models, industrial time-series models, geospatial and Earth-observation models, biological and healthcare models, and public-sector decision-support applications. Particular attention is given to transfer learning, multimodal learning, domain adaptation, predictive analytics, simulation, and AI-assisted scientific discovery. The analysis indicates that foundation models can potentially reduce the cost of developing specialised AI systems, improve cross-domain knowledge transfer, accelerate scientific analysis, and support more adaptive decision-making. Nevertheless, significant challenges remain concerning data governance, model reliability, domain-specific validation, computational costs, explainability, cybersecurity, intellectual property, and responsible deployment. The study concludes that the next phase of foundation-model development will increasingly involve models designed not merely to generate content but to understand complex systems, analyse scientific observations, predict future states, and support high-impact decisions.

Keywords: Foundation Models, Artificial Intelligence, Scientific AI, Machine Learning, Multimodal AI, Industry 4.0, Public Services, Predictive Analytics, Digital Transformation, Domain-Specific AI.

1. Introduction

Artificial Intelligence has traditionally been developed through task-specific models. A model might be trained to classify images, predict equipment failures, identify fraudulent transactions, or translate text. Such systems are generally designed around a particular dataset and objective.

The emergence of foundation models represents a different approach. Rather than developing an independent model for every task, foundation models are trained on broad datasets and can subsequently be adapted to multiple applications.

The concept became particularly prominent with large language models and generative AI. However, restricting foundation models to text generation or content creation significantly understates their potential.

Foundation-model principles can be applied to many forms of information, including:

- Scientific measurements.
- Genomic sequences.
- Satellite imagery.
- Weather observations.
- Industrial sensor data.
- Financial time series.
- Medical records.
- Traffic patterns.
- Environmental observations.

This development is creating a broader category of general-purpose or reusable AI representations for complex domains.

In science, foundation models can help analyse protein structures, climate patterns, astronomical observations, chemical interactions, and scientific literature. In industry, they can support predictive maintenance, robotics, manufacturing optimisation, forecasting, and quality control. In public services, they can potentially assist disaster management, urban planning, infrastructure monitoring, public-health planning, and administrative decision support.

The central argument of this study is that the future significance of foundation models will not depend exclusively on their ability to generate content. Their greater long-term contribution may lie in their capacity to learn representations of complex real-world systems and support prediction, simulation, classification, optimisation, and scientific reasoning.

2. Understanding Foundation Models

A foundation model is a machine-learning model trained on broad and often large-scale datasets that can subsequently be adapted to a variety of downstream tasks.

The general architecture can be represented as:

Large-scale data → Pre-training → General representation → Adaptation → Domain-specific applications

Unlike conventional machine-learning systems, foundation models can potentially support multiple downstream applications from the same underlying model.

For example, a scientific model trained on large quantities of molecular information could potentially support molecular-property prediction, protein analysis, drug discovery, and biological research.

3. Foundation Models Beyond Generative AI

Generative AI focuses primarily on creating new content.

Foundation models, however, can perform several other functions.

3.1 Prediction

Models can predict future system states based on historical observations.

3.2 Classification

Models can identify categories or conditions in complex datasets.

3.3 Representation Learning

Models can transform complex raw data into useful representations.

3.4 Anomaly Detection

Models can identify patterns that differ significantly from normal system behaviour.

3.5 Simulation

Models can approximate complex systems and evaluate potential scenarios.

3.6 Decision Support

Models can combine multiple information sources to assist human decision-making.

Therefore, foundation models should be viewed as a broader AI infrastructure rather than simply a technology for generating text or images.

4. Research Objectives

The objectives of this study are:

1. To explain the evolution and characteristics of foundation models.
2. To examine applications beyond conventional generative AI.
3. To analyse applications across scientific research and discovery.
4. To investigate industrial applications of foundation models.

5. To explore applications in public services and governance.
6. To identify technical, ethical, regulatory, and operational challenges.
7. To examine future directions for foundation-model development.

5. Research Methodology

This study adopts a qualitative and descriptive research methodology based on secondary sources.

Academic publications, research papers, technical reports, institutional publications, and policy literature concerning foundation models, scientific AI, industrial AI, multimodal learning, and public-sector digital transformation are reviewed.

The study organises applications into three broad domains:

1. **Science and research**
2. **Industry and commercial systems**
3. **Public services and government**

A thematic analysis is then used to identify emerging opportunities, limitations, and future research directions.

6. Foundation Models for Scientific Discovery

Science generates increasingly large quantities of complex data.

Examples include:

- Genomic sequences.
- Protein structures.
- Particle-physics observations.
- Astronomical images.
- Chemical measurements.
- Climate observations.
- Oceanographic data.
- Earth-observation imagery.

Traditional scientific analysis often requires specialised models for each dataset.

Foundation models offer the possibility of developing reusable models capable of learning general representations across related scientific datasets.

7. Biological and Healthcare Foundation Models

Biology is particularly suitable for foundation-model approaches because biological systems generate large and highly structured datasets.

7.1 Protein and Molecular Analysis

Foundation models can learn patterns from protein sequences, structures, and molecular information.

These representations may support:

- Protein-function prediction.
- Molecular-property prediction.
- Protein design.
- Drug discovery.
- Biological interaction analysis.

The success of models such as AlphaFold has demonstrated the potential of AI to address complex biological problems.

7.2 Clinical Data

Healthcare foundation models may integrate:

- Medical records.
- Medical imaging.
- Laboratory measurements.
- Genomic data.
- Clinical notes.
- Physiological signals.

Such models could support risk prediction, clinical decision support, disease classification, and patient stratification.

However, healthcare applications require particularly rigorous validation because model errors can directly affect patient outcomes.

8. Scientific Foundation Models for Earth and Climate Systems

Climate and Earth systems produce massive quantities of spatiotemporal data.

Foundation models can potentially process:

- Satellite imagery.
- Weather observations.
- Atmospheric measurements.
- Ocean data.
- Land-use information.
- Climate simulations.

Potential applications include:

- Weather forecasting.
- Climate-risk assessment.
- Flood prediction.
- Drought monitoring.
- Wildfire detection.
- Agricultural monitoring.
- Environmental change analysis.

Unlike generative applications, these systems focus primarily on understanding and predicting physical processes.

9. Foundation Models in Astronomy and Space Science

Astronomical research involves enormous datasets from telescopes and space-based instruments.

Foundation models can assist in:

- Object classification.
- Galaxy identification.
- Anomaly detection.
- Spectral analysis.
- Event detection.
- Large-scale astronomical data processing.

The ability to learn general representations from astronomical observations could reduce the need to create separate models for each scientific dataset.

10. Chemistry and Materials Science

Foundation models can analyse chemical structures and material properties.

Potential applications include:

- Materials discovery.
- Catalyst optimisation.
- Battery-material research.
- Molecular-property prediction.
- Chemical reaction analysis.
- Semiconductor research.

AI can help researchers narrow the search space by identifying promising materials before laboratory testing.

This creates a potential AI → prediction → laboratory validation → new data → model improvement cycle.

11. Foundation Models in Industry

Industrial systems generate large volumes of operational data through sensors, machines, enterprise systems, and connected equipment.

Foundation models can potentially learn general patterns across industrial processes.

11.1 Predictive Maintenance

Industrial foundation models can analyse:

- Vibration.
- Temperature.
- Pressure.
- Acoustic signals.
- Machine logs.
- Maintenance records.

The objective is to identify patterns associated with equipment deterioration.

11.2 Manufacturing Optimisation

Models can support:

- Production scheduling.
- Quality control.
- Process optimisation.
- Defect detection.
- Energy optimisation.

11.3 Industrial Robotics

Foundation models may provide robots with more general representations of objects, environments, tasks, and physical interactions.

This may reduce the need to program separate systems for every industrial task.

12. Time-Series Foundation Models

A particularly important emerging area is the development of foundation models for time-series data.

Time-series information occurs in:

- Energy consumption.
- Financial markets.
- Industrial sensors.
- Traffic systems.
- Weather.
- Healthcare monitoring.
- Telecommunications.

A time-series foundation model could potentially be adapted to multiple forecasting tasks without being developed entirely from scratch for every application.

This may become one of the most important applications of foundation models outside generative AI.

13. Geospatial Foundation Models

Geospatial foundation models are designed to understand information associated with location and spatial relationships.

They can combine:

- Satellite imagery.
- Geographic information systems.
- Weather information.
- Infrastructure data.
- Population information.

- Land-use data.

Applications include:

- Urban planning.
- Disaster management.
- Agricultural monitoring.
- Infrastructure assessment.
- Environmental conservation.
- Climate adaptation.

14. Foundation Models for Public Services

Public-sector organisations generate and manage large quantities of administrative and operational data.

Foundation models may support public services in areas such as:

- Disaster management.
- Public health.
- Transportation.
- Infrastructure management.
- Environmental monitoring.
- Social-service planning.
- Public administration.

However, government applications require particularly strong governance because decisions may affect citizens' rights, access to services, and public resources.

15. Disaster Management

Foundation models can integrate diverse information sources such as:

- Satellite imagery.
- Weather observations.
- Emergency reports.
- Infrastructure data.
- Population information.
- Historical disaster records.

This can support early-warning systems and emergency planning.

For example, a geospatial foundation model could analyse satellite imagery and environmental information to identify regions at increased risk of flooding.

16. Smart Cities and Urban Systems

Cities produce enormous amounts of data through transportation systems, energy networks, public infrastructure, environmental sensors, and administrative systems.

Foundation models can potentially provide a common analytical layer across these datasets.

Potential applications include:

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- Traffic prediction.
- Energy optimisation.
- Waste-management planning.
- Infrastructure monitoring.
- Air-quality analysis.
- Urban-growth modelling.

The integration of multiple datasets can provide a more comprehensive representation of urban systems.

Table 1. Foundation Models Beyond Generative AI

Domain	Data Type	Foundation-Model Application	Potential Outcome
Biology	Genomic sequences	Biological representation learning	Improved research
Healthcare	Clinical data	Risk prediction	Decision support
Climate	Weather observations	Forecasting	Better preparedness
Earth Science	Satellite imagery	Geospatial analysis	Environmental monitoring
Astronomy	Telescope data	Object detection	Scientific discovery
Industry	Sensor streams	Predictive maintenance	Reduced downtime
Manufacturing	Images + sensors	Quality analysis	Improved production
Energy	Time-series data	Demand forecasting	Grid optimisation
Government	Administrative data	Policy analysis	Improved services
Disaster Management	Multi-source data	Risk prediction	Faster response

17. Multimodal Foundation Models

Real-world systems rarely consist of a single type of data.

For example, infrastructure management may require:

- Images.
- Sensor data.
- Engineering reports.
- Geographic information.
- Weather data.

Multimodal foundation models can potentially integrate these different information types.
This is particularly important for complex decision-making because combining multiple sources can provide a more complete representation of a real-world system.

18. Foundation Models and Digital Twins

Digital twins represent physical assets or systems in digital environments.
Foundation models could enhance digital twins by analysing large quantities of historical and real-time information.
For example, an intelligent infrastructure digital twin could combine:
Sensors + satellite imagery + maintenance records + weather data + foundation model
The resulting system could predict infrastructure deterioration and evaluate alternative intervention strategies.
This could transform digital twins from passive visualisation systems into predictive decision-support platforms.

19. Foundation Models and Scientific Automation

One of the most promising future developments is the integration of foundation models with automated scientific experimentation.
A potential cycle could be:
Data → AI hypothesis → Experimental design → Laboratory experiment → New data → Model update
Such systems could accelerate research by allowing AI to identify promising experimental directions.
Human researchers would remain responsible for scientific validation and interpretation.

20. Data Analysis

The comparative analysis suggests that foundation models have particularly strong potential in domains where:

1. Large datasets are available.
2. Data contain recurring patterns.
3. Multiple downstream tasks exist.
4. Domain adaptation is possible.
5. Continuous data generation enables model improvement.

Science, industry, and public services all meet several of these conditions.
However, the effectiveness of foundation models varies substantially between domains. A model trained on general data may perform poorly when applied to highly specialised scientific or industrial environments.
Domain-specific adaptation is therefore likely to remain important.

Table 2. Potential Strategic Value of Foundation Models

Application	Strategic Potential (%)
Scientific Discovery	94
Healthcare Decision Support	92
Climate and Earth Observation	93
Industrial Predictive Maintenance	91
Manufacturing Optimisation	90
Energy Forecasting	89
Smart-City Management	88
Disaster Risk Management	93
Public-Service Decision Support	87
Environmental Monitoring	91

Note: These percentages are illustrative analytical indicators intended for conceptual comparison and are not empirical measurements from a specific dataset.

21. Key Challenges

21.1 Data Quality

Foundation models require high-quality datasets. Poor or biased data can produce unreliable representations.

21.2 Domain Adaptation

A model developed in one domain may not automatically transfer effectively to another.

21.3 Computational Cost

Training large foundation models can require substantial computing resources, energy, and specialised infrastructure.

21.4 Explainability

Decision-makers may require explanations for predictions produced by complex models.

21.5 Hallucination and Reliability

Where foundation models produce predictions or recommendations, inaccurate outputs can have significant consequences.

21.6 Cybersecurity

Models and their underlying data may become targets for manipulation or adversarial attacks.

21.7 Intellectual Property

Questions remain regarding ownership and permitted use of training datasets, model outputs, and domain-specific adaptations.

21.8 Regulatory Uncertainty

Regulatory systems are still developing approaches to general-purpose and domain-specific AI models.

22. Ethical Considerations

Foundation models can influence high-impact decisions.
In healthcare, incorrect predictions may affect treatment.
In public services, biased models could influence access to resources.
In industry, incorrect recommendations could create safety risks.
Therefore, responsible deployment should include:

- Human oversight.
- Independent validation.
- Bias assessment.
- Data governance.
- Audit mechanisms.
- Security controls.
- Clear accountability.

Foundation models should be treated as decision-support technologies rather than automatically authoritative decision-makers.

23. Future Directions

23.1 Scientific Foundation Models

Future models may increasingly be trained specifically on scientific datasets and physical laws.

23.2 World and Physical-System Models

Models may increasingly represent physical environments rather than merely language or visual content.

23.3 Smaller Domain-Specific Models

Highly specialised models may provide better efficiency and reliability than extremely large general-purpose models in certain applications.

23.4 Edge Foundation Models

Models may increasingly operate directly on industrial machines, vehicles, sensors, and other edge devices.

23.5 Continual Learning

Future systems may continuously learn from new observations while maintaining appropriate safeguards against model degradation.

23.6 Human-AI Scientific Collaboration

Researchers may use foundation models as analytical partners for hypothesis generation, simulation, data interpretation, and experimental planning.

24. Policy Recommendations

1. Establish sector-specific AI governance

Healthcare, energy, transportation, science, and public administration have different risk profiles and therefore require tailored governance.

2. Invest in public-interest datasets

Governments and research institutions should develop high-quality datasets for scientific and public-service applications.

3. Develop AI evaluation standards

Foundation models should undergo domain-specific testing before deployment in high-impact environments.

4. Promote open scientific collaboration

Researchers should be encouraged to share benchmarks, evaluation methods, and reproducible scientific AI research where appropriate.

5. Strengthen computational infrastructure

Public research institutions require access to appropriate computing resources to avoid excessive dependence on a small number of technology providers.

6. Develop interdisciplinary education

Future AI professionals will require knowledge of both computational methods and domain-specific science or industry.

25. Questionnaire

5-Point Likert Scale: 1 = Strongly Disagree, 5 = Strongly Agree

No.	Statement
1	Foundation models have applications beyond generative AI.
2	Foundation models can accelerate scientific research.
3	Scientific foundation models can improve data analysis.
4	Foundation models can improve industrial predictive maintenance.
5	Foundation models can support climate and environmental monitoring.
6	Foundation models can improve public-service decision support.
7	Domain-specific validation is necessary before deploying foundation models.
8	Human oversight should remain important in high-impact applications.
9	Governments should establish sector-specific governance frameworks for foundation models.
10	Foundation models will become important infrastructure for future AI systems.

26. Discussion

The analysis demonstrates that foundation models represent a broader technological transition than the generative-AI applications that initially attracted public attention.

The most important emerging opportunity is the development of models that learn representations of complex real-world systems.

In science, this may involve understanding molecules, proteins, climate processes, astronomical observations, or physical systems. In industry, it may involve understanding machines, manufacturing processes, energy networks, and supply chains. In public services, it may involve analysing infrastructure, environmental conditions, transportation systems, and population-level information.

This transition can be understood as a movement from:

AI that generates content → AI that understands and predicts systems.

However, this does not mean that foundation models will automatically outperform specialised models. In high-stakes environments, smaller domain-specific models may sometimes be more reliable, interpretable, efficient, and easier to validate.

Consequently, future AI architectures are likely to involve combinations of foundation models, specialised models, traditional statistical methods, physical simulations, and human expertise.

27. Conclusion

Foundation models represent an important development in Artificial Intelligence whose significance extends far beyond generative content creation. Their ability to learn broad representations from large and diverse datasets creates opportunities for scientific discovery, industrial optimisation, healthcare, environmental monitoring, infrastructure management, and public services.

Scientific foundation models can support biological research, climate prediction, astronomy, chemistry, and materials science. Industrial models can analyse sensor data, optimise manufacturing, predict equipment failures, and support robotics. Public-sector applications include disaster management, smart cities, environmental monitoring, infrastructure management, and decision support.

Nevertheless, the adoption of foundation models presents significant challenges. Data quality, domain adaptation, computational cost, explainability, cybersecurity, intellectual property, reliability, and regulatory uncertainty must be addressed.

The future of foundation models is therefore likely to extend from content generation towards system understanding, prediction, simulation, and decision support. Their greatest value may emerge when they are integrated with scientific knowledge, physical models, domain-specific data, digital twins, and human expertise.

A responsible and interdisciplinary approach will be essential to ensure that foundation models contribute to scientific progress, industrial productivity, and improved public services while maintaining safety, accountability, transparency, and public trust.

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