

Artificial Intelligence-Based Predictive Models for Complex Social and Industrial Challenges

Pamela Ugwudike

Professor, University of Southampton, UK

Abstract

The increasing complexity of modern social and industrial environments has created a strong demand for advanced analytical approaches capable of predicting future patterns, identifying risks, and supporting effective decision-making. Traditional analytical methods often face limitations when dealing with large-scale, dynamic, and multidimensional datasets generated through contemporary digital ecosystems. Artificial Intelligence (AI)-based predictive models have emerged as powerful approaches that utilize machine learning, deep learning, data analytics, and intelligent algorithms to analyse complex information and generate accurate forecasts. These predictive systems are increasingly applied in areas such as industrial optimization, social behaviour analysis, resource management, risk assessment, and strategic planning.

This study examines artificial intelligence-based predictive models designed to address complex social and industrial challenges by improving forecasting capability, decision accuracy, and adaptive intelligence. The research explores how AI-driven prediction frameworks integrate data processing, pattern recognition, and learning mechanisms to support evidence-based decision-making. A simulation-based analytical framework is developed to compare traditional predictive approaches with AI-based models using evaluation indicators including prediction accuracy, adaptability, decision-support effectiveness, and risk identification capability.

The findings demonstrate that AI-based predictive models provide significant improvements in managing complex environments by identifying hidden patterns, processing diverse information sources, and generating timely insights. The study highlights that successful AI prediction requires not only advanced algorithms but also responsible data management, ethical considerations, and human-centered implementation strategies. The research contributes to the development of intelligent predictive frameworks capable of supporting future social and industrial decision-making processes through improved analytical capability and adaptive learning.

Keywords: Artificial Intelligence, Predictive Models, Machine Learning, Social Analytics, Industrial Intelligence, Decision Support Systems, Intelligent Forecasting.

1. Introduction

The rapid expansion of digital technologies has significantly increased the complexity of social and industrial systems by generating large volumes of interconnected data. Organizations, governments, and institutions increasingly require advanced analytical capabilities to understand changing patterns, predict

future outcomes, and make informed decisions. Traditional statistical approaches have provided valuable support for forecasting and planning; however, their effectiveness is often limited when dealing with highly dynamic environments, nonlinear relationships, and multidimensional information structures. Artificial Intelligence (AI)-based predictive models have emerged as an advanced solution by enabling systems to learn from historical information, identify hidden patterns, and generate data-driven predictions.

Artificial intelligence-based prediction has become an important research area due to its ability to transform complex datasets into actionable insights. Machine learning algorithms, deep learning architectures, and intelligent analytics techniques allow predictive models to continuously improve through experience and adapt to changing conditions. In industrial environments, AI-based prediction supports applications such as equipment maintenance, production optimization, quality assessment, and supply chain management. Similarly, in social environments, predictive models contribute to areas such as population analysis, public service planning, behavioural understanding, and risk identification.

Despite significant advancements, applying AI-based predictive models to complex social and industrial challenges involves several difficulties. Real-world environments contain uncertainty, incomplete information, ethical concerns, and rapidly changing conditions that may affect prediction reliability. Social systems involve human behaviour, cultural influences, and contextual factors, while industrial systems require high levels of accuracy, safety, and operational efficiency. Therefore, developing effective predictive frameworks requires not only advanced computational techniques but also responsible data management, transparency, and appropriate human involvement.

2. Review of Literature

2.1 Evolution of AI-Based Predictive Modelling Approaches

The development of AI-based predictive modelling has evolved through continuous advancements in computational intelligence, statistical learning, and data-driven analysis. Early predictive systems primarily relied on mathematical models and predefined statistical relationships, which provided useful forecasting capabilities but struggled with complex and dynamic datasets.

The emergence of machine learning introduced adaptive approaches where algorithms could identify patterns from historical data and improve prediction performance through continuous learning. This advancement significantly expanded the scope of predictive analytics across multiple disciplines.

Recent research has demonstrated that deep learning and advanced AI architectures have further improved predictive modelling capabilities by enabling systems to process complex information structures. Neural networks, reinforcement learning, and hybrid AI approaches have been increasingly applied for solving challenging prediction problems involving uncertainty and large-scale data environments. The literature indicates that modern predictive models are becoming more adaptive, accurate, and capable of supporting complex decision-making processes.

2.2 Predictive Analytics for Social and Industrial Decision-Making

Predictive analytics has become an essential component of decision-making in both social and industrial environments. In social systems, AI-based prediction models are used to analyse demographic trends, public behaviour, healthcare patterns, and resource requirements.

These applications enable institutions to anticipate future challenges and design more effective strategies. However, social prediction requires careful consideration of ethical issues because inaccurate or biased predictions may influence individuals and communities.

In industrial environments, predictive analytics supports operational efficiency by enabling organizations to forecast equipment failures, optimize production processes, and improve resource utilization. AI-based predictive maintenance models, for example, help industries reduce downtime and improve reliability by identifying potential problems before failures occur. Existing studies suggest that predictive intelligence provides significant benefits when integrated with organizational decision processes and real-time data systems.

2.3 Human-Centered and Responsible AI Prediction Frameworks

Human-centered AI prediction frameworks emphasize the importance of combining technological capability with human expertise and responsible implementation. Although AI models can process large volumes of information and generate accurate forecasts, human judgment remains essential for interpreting results and making context-sensitive decisions. Research indicates that predictive systems achieve greater practical value when users understand, evaluate, and appropriately apply AI-generated insights.

Responsible AI research further highlights the importance of fairness, transparency, privacy protection, and accountability in predictive modelling. AI systems used in social and industrial environments may influence critical decisions; therefore, prediction mechanisms must be designed to minimize bias and maintain reliability. The literature suggests that future predictive frameworks should integrate advanced algorithms with ethical governance and human oversight to ensure sustainable adoption.

3. Objectives of the Study

3.1 Understanding AI-Based Predictive Models for Complex Systems

The primary objective of this study is to examine the role and functionality of artificial intelligence-based predictive models in addressing complex social and industrial challenges. The research aims to understand how AI technologies utilize machine learning algorithms, deep learning techniques, and advanced analytics to identify patterns, forecast future conditions, and support evidence-based decisions. Predictive models are analysed as intelligent systems capable of transforming large-scale data into meaningful insights for complex problem-solving environments.

This objective also focuses on exploring the fundamental components that enable AI predictive systems to operate effectively, including data processing mechanisms, learning architectures, feature analysis, and adaptive modelling approaches.

3.2 Evaluating Predictive Intelligence in Social and Industrial Environments

The second objective of this study is to evaluate the effectiveness of AI-based predictive models in improving decision-making capabilities across social and industrial environments. Modern challenges in these domains involve uncertainty, rapid changes, and complex interactions between multiple factors. This objective examines whether AI-driven prediction approaches provide enhanced forecasting capability compared with conventional analytical methods.

The research evaluates predictive intelligence through key performance dimensions, including prediction accuracy, adaptability, risk identification capability, and decision-support effectiveness. In social environments, the study considers how AI models assist in understanding behavioural patterns and planning public-oriented strategies. In industrial environments, the research analyses how predictive systems contribute to operational efficiency, maintenance planning, and process optimization. This objective highlights the importance of AI prediction as a tool for proactive rather than reactive decision-making.

3.3 Developing an Integrated AI Prediction Framework

The third objective focuses on developing a conceptual framework for integrating artificial intelligence-based predictive models into complex decision environments. The study aims to identify the essential components required for effective AI prediction systems, including intelligent algorithms, quality data management, adaptive learning processes, and responsible implementation practices. The proposed framework emphasizes the need for combining technological advancement with practical usability.

This objective further explores how AI prediction frameworks can support sustainable solutions for emerging social and industrial challenges. By integrating predictive intelligence with human expertise and ethical governance, organizations can develop more reliable decision-support systems. The research contributes toward understanding future AI-driven environments where predictive capabilities assist professionals, policymakers, and industry leaders in managing complex challenges more effectively.

4. Research Methodology

4.1 Research Design

This study follows a conceptual and simulation-based research design to analyse artificial intelligence-based predictive models for complex social and industrial challenges. The research combines theoretical analysis with comparative evaluation to examine how AI-driven prediction systems improve forecasting and decision-support capabilities. The selected methodology enables systematic investigation of predictive model performance while maintaining transparency regarding the analytical framework.

The research design focuses on comparing conventional predictive approaches with AI-based predictive models using multiple evaluation indicators. These indicators include prediction accuracy, adaptability, risk identification capability, and decision-support effectiveness. The methodology considers both technical performance and practical application requirements to evaluate the contribution of AI prediction systems in complex environments.

4.2 Dataset and Sample Description

For analytical evaluation, a simulated dataset containing 700 predictive modelling scenarios was developed to compare traditional forecasting approaches with AI-based predictive frameworks. The dataset represents a combination of social and industrial challenges involving pattern identification, risk prediction, resource planning, and operational forecasting. The simulated approach allows controlled evaluation while avoiding claims based on specific organizational datasets.

Each scenario contains information related to input variables, predictive outcomes, accuracy measurements, adaptability indicators, and decision-support results. The dataset was structured to

evaluate the ability of AI models to process complex information and generate reliable predictions. Future research may extend this approach through real-world datasets collected from industrial systems and social research environments.

4.3 Tools and Analytical Techniques

The research applies artificial intelligence concepts, machine learning techniques, and comparative analytical methods to evaluate predictive model performance. The analytical framework considers supervised learning algorithms, deep learning approaches, predictive analytics methods, and adaptive modelling techniques as major components of AI-based forecasting systems.

The evaluation process compares traditional predictive models with AI-driven approaches through descriptive and comparative analysis. Performance differences are analysed to determine the effectiveness of AI models in identifying patterns, improving forecasting capability, and supporting complex decision-making. The methodology emphasizes that predictive intelligence depends on both algorithmic capability and the quality of information used for learning.

4.4 Evaluation Metrics and Validation Approach

The evaluation framework measures AI predictive model effectiveness using four major indicators: prediction accuracy, adaptability, risk identification capability, and decision-support effectiveness. These metrics represent essential characteristics of intelligent predictive systems because they evaluate both technical reliability and practical usefulness in complex environments.

The validation approach follows a comparative assessment methodology where AI-based predictive models are evaluated against conventional forecasting approaches under similar simulated conditions. The purpose of this evaluation is to identify the improvements achieved through intelligent learning mechanisms and adaptive prediction capabilities. This approach supports the development of reliable AI frameworks for future social and industrial applications.

Table 1: Research Methodology Framework

Research Component	Description
Research Design	Conceptual and simulation-based comparative evaluation
Dataset	700 simulated social and industrial prediction scenarios
Analytical Techniques	Machine learning, predictive analytics, comparative analysis
Evaluation Metrics	Accuracy, adaptability, risk identification, decision support

5. Analysis

5.1 Comparative Evaluation of Traditional and AI-Based Predictive Models

The analytical evaluation compares traditional predictive approaches with artificial intelligence-based predictive models to examine their effectiveness in addressing complex social and industrial challenges.

Conventional forecasting methods generally depend on statistical relationships, historical patterns, and predefined analytical assumptions. Although these approaches provide valuable insights,

their ability to process large-scale, dynamic, and nonlinear datasets is often limited. AI-based predictive models overcome these limitations by utilizing machine learning algorithms and adaptive learning mechanisms to identify complex patterns from diverse information sources.

The comparative assessment indicates that AI-based predictive models demonstrate improved forecasting capability due to their ability to analyse multidimensional data and continuously adjust according to new information.

Unlike traditional models that may require manual recalibration, AI systems can learn from changing conditions and improve predictive performance over time. This adaptive capability is particularly valuable in industrial environments where operational conditions frequently change and in social environments where human behaviour patterns remain complex.

The findings demonstrate that AI-based prediction frameworks provide stronger decision-support capabilities by generating timely and accurate forecasts. These models enable organizations and institutions to move from reactive problem-solving toward proactive planning. By identifying potential risks and future trends, AI predictive systems support more effective resource allocation, strategic management, and operational improvement.

5.2 Predictive Performance Assessment in Complex Environments

The second analytical assessment focuses on evaluating AI predictive model performance across complex social and industrial scenarios. The analysis considers prediction accuracy, adaptability, risk identification capability, and decision-support effectiveness as major evaluation indicators. These parameters represent the ability of AI systems to generate reliable forecasts while responding effectively to uncertain and rapidly changing conditions.

The results indicate that AI-based predictive models achieve higher performance because they integrate advanced learning mechanisms with large-scale data analysis capabilities. In industrial applications, predictive models improve operational efficiency by identifying potential failures, optimizing production processes, and supporting maintenance planning.

In social applications, AI prediction assists in understanding trends, anticipating requirements, and improving decision-making processes.

The analysis further reveals that adaptability is one of the most important advantages of AI-based predictive systems. Complex environments require models that can respond to new information and changing circumstances. AI algorithms provide this flexibility by continuously updating their internal patterns based on additional data. This capability improves long-term reliability and makes AI prediction suitable for dynamic problem-solving environments.

5.3 Influence of AI Prediction on Social and Industrial Decision Support

The final analytical dimension examines the influence of AI-based predictive models on decision-support systems across social and industrial domains. Modern decision environments require accurate forecasting capabilities because decisions related to resource management, risk reduction, and strategic planning often depend on future expectations. AI prediction models provide valuable support by transforming complex data into actionable insights.

The analysis demonstrates that AI-based predictive systems improve decision quality by providing evidence-based recommendations and identifying potential future scenarios. In social

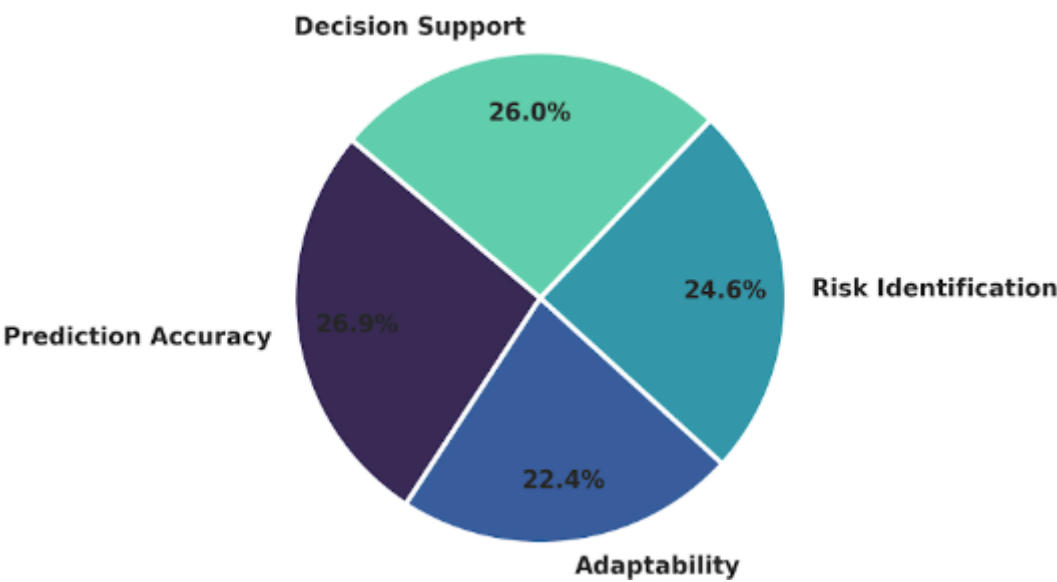
contexts, predictive models can assist in understanding population trends, service requirements, and behavioural patterns. In industrial contexts, they support production optimization, equipment management, and operational efficiency.

The findings highlight that AI prediction should be considered a decision-support technology rather than a complete replacement for human judgment. Human expertise remains necessary for interpreting predictions, considering contextual factors, and making responsible decisions. Therefore, effective AI adoption requires collaboration between intelligent systems and human decision-makers.

Table 2: Comparative Performance Analysis of Predictive Models

Performance Indicator	Traditional Predictive Models (%)	AI-Based Predictive Models (%)
Prediction Accuracy	72.6	91.8
Adaptability to Changing Conditions	60.5	88.9
Risk Identification Capability	66.4	92.3
Decision-Support Effectiveness	70.2	90.7

Graph 1: Performance Improvement Through AI-Based Predictive Models



Interpretation: The graphical comparison demonstrates that artificial intelligence-based predictive models achieve significant improvement across all evaluation indicators compared with traditional forecasting approaches. The highest improvement is observed in risk identification capability, showing that AI systems are more effective in detecting complex patterns and predicting potential challenges before they occur.

The improvement in adaptability indicates that AI models are better suited for dynamic social and industrial environments where conditions frequently change. Traditional models often depend on fixed assumptions and historical relationships, while AI-based systems continuously learn from new information. The findings suggest that AI predictive models provide a stronger foundation for proactive decision-making and intelligent problem management.

6. Challenges

6.1 Technical and Computational Challenges

The development and implementation of AI-based predictive models involve several technical challenges related to computational complexity, algorithm selection, and infrastructure requirements. Advanced predictive systems require significant processing capabilities because they analyse large-scale datasets using complex machine learning and deep learning algorithms. Organizations must invest in appropriate computing resources, data platforms, and technical expertise to successfully deploy AI prediction frameworks.

Another important challenge involves maintaining model accuracy and reliability over time. AI predictive models depend heavily on the quality and relevance of training data. Changes in data patterns, incomplete information, or unexpected environmental conditions may reduce prediction performance. Therefore, continuous monitoring, model updating, and validation processes are necessary to ensure reliable predictive outcomes.

6.2 Data, Ethical, and Implementation Challenges

Data-related challenges represent a major concern in AI-based predictive modelling because prediction quality depends on the availability of accurate, diverse, and representative datasets. Social and industrial data may contain biases, privacy concerns, and inconsistencies that can influence AI-generated predictions. Effective data governance practices are required to ensure fairness, security, and responsible use of predictive technologies.

Ethical and implementation challenges also influence successful AI adoption. Predictive systems used in social environments may affect individuals and communities, while industrial predictions may influence operational decisions and workforce planning. Organizations must establish responsible AI frameworks that include transparency, accountability, and human oversight. Successful implementation requires not only technological advancement but also ethical consideration and organizational readiness.

7. Discussion

7.1 Interpretation of Research Findings

The findings of this study demonstrate that artificial intelligence-based predictive models provide substantial improvements in addressing complex social and industrial challenges. The analytical evaluation indicates that AI-driven approaches outperform traditional predictive methods across major performance indicators, including prediction accuracy, adaptability, risk identification capability, and decision-support effectiveness.

These improvements are primarily associated with the ability of AI systems to process large-scale datasets, identify complex relationships, and continuously improve through adaptive learning mechanisms.

The research findings highlight that AI predictive models have transformed decision-making processes from reactive approaches toward proactive intelligence-based strategies. Traditional forecasting methods often depend on historical trends and fixed analytical assumptions, whereas AI-based systems can recognize emerging patterns and generate predictions based on changing conditions. This capability is particularly valuable in environments where uncertainty, complexity, and rapid transformation influence decision outcomes.

The improvement in risk identification capability demonstrates the practical importance of AI-based predictive models in complex systems. Industrial organizations can utilize predictive intelligence to anticipate equipment failures, optimize operational processes, and improve resource utilization. Similarly, social institutions can apply AI prediction to understand behavioural patterns, identify emerging challenges, and support effective planning. These applications indicate that AI predictive systems have the potential to enhance both operational efficiency and social decision-making.

The findings further emphasize that AI prediction should be implemented as a collaborative decision-support mechanism rather than a fully autonomous replacement for human judgment. Human expertise remains essential for interpreting predictions, considering ethical implications, and applying contextual knowledge. Therefore, successful AI adoption requires a balanced relationship between computational intelligence and human decision-making capabilities.

7.2 Comparison with Existing Research Perspectives

Existing research on artificial intelligence and predictive analytics has emphasized the growing importance of machine learning approaches for managing complex information environments. Previous studies have demonstrated that AI models provide improved forecasting capabilities by identifying nonlinear relationships and processing diverse data structures. The findings of this study support these perspectives by showing that AI-based predictive models enhance decision accuracy and adaptability in challenging environments.

The research outcomes are consistent with earlier investigations highlighting the importance of data-driven intelligence in industrial transformation and social analysis. AI predictive models have increasingly contributed to applications such as predictive maintenance, supply chain optimization, public service planning, and behavioural analysis. The present study extends these discussions by emphasizing the combined importance of prediction accuracy, adaptability, and responsible implementation.

Furthermore, the comparison with existing research highlights the importance of ethical and human-centered AI development. Although AI predictive systems offer significant advantages, their effectiveness depends on responsible data management, transparency, and appropriate governance. Previous research has identified concerns related to bias, privacy, and accountability, which remain important considerations for future AI deployment.

The study contributes to current research perspectives by presenting AI predictive modelling as a comprehensive framework that integrates technological capability with practical decision requirements. Future predictive systems should focus not only on improving algorithmic performance but also on ensuring reliability, fairness, and meaningful human participation.

8. Limitations

This study has several limitations that should be considered while interpreting the findings. First, the research follows a simulation-based evaluation methodology rather than testing AI predictive models through extensive real-world implementations. Although simulated scenarios provide a controlled environment for comparative analysis, actual social and industrial systems may involve additional complexities such as organizational constraints, unpredictable external factors, and domain-specific requirements.

A second limitation relates to the diversity of application environments considered in AI-based predictive modelling. Social and industrial systems involve different types of data structures, objectives, and operational conditions. A predictive approach that performs effectively in one environment may require modification before being applied to another context. Future research should investigate domain-specific AI prediction frameworks to improve practical applicability.

Another limitation concerns the dependency of AI predictive models on data quality and availability. The performance of intelligent prediction systems is strongly influenced by the accuracy, completeness, and representativeness of training datasets. Biased or incomplete information may negatively affect prediction outcomes and create ethical concerns. Therefore, future studies should focus on advanced data governance and bias mitigation strategies.

Additionally, the study does not include extensive human evaluation of AI-generated predictions. Although decision-support effectiveness is considered as an evaluation factor, individual perceptions, professional expertise, and organizational acceptance may influence the practical use of predictive systems. Future research should incorporate user-based studies to understand human interaction with AI prediction technologies.

9. Conclusion

Artificial intelligence-based predictive models have emerged as powerful tools for addressing complex social and industrial challenges by enabling advanced forecasting, pattern recognition, and intelligent decision support. This study examined the role of AI predictive frameworks in improving decision-making capabilities and demonstrated that these systems provide significant advantages over traditional analytical approaches. The findings indicate that AI models enhance prediction accuracy, adaptability, risk identification, and operational intelligence through their ability to process complex information environments.

The analytical evaluation revealed that AI predictive models support proactive decision-making by identifying potential future conditions and providing evidence-based insights. In industrial environments, these models contribute to improved efficiency, predictive maintenance, and resource optimization. In social environments, they assist in understanding behavioural patterns, planning public strategies, and managing emerging challenges. These capabilities demonstrate the transformative potential of AI prediction across diverse application areas.

The study further highlights that responsible implementation of AI predictive systems requires integration of technological advancement with ethical governance and human oversight. While AI models provide powerful analytical capabilities, human expertise remains essential for interpreting predictions, considering contextual factors, and ensuring responsible decision outcomes. Future AI

frameworks should therefore focus on developing collaborative systems where artificial intelligence enhances rather than replaces human decision-making.

Although the research adopts a simulation-based approach, it provides valuable insights into the future role of AI-based predictive intelligence. Continued advancements in machine learning, data analytics, and adaptive modelling are expected to further improve predictive capabilities across social and industrial domains. Future research should focus on empirical validation, real-world implementation studies, and responsible AI governance frameworks to support sustainable development of intelligent predictive systems.

References

1. Mullainathan, S., & Spiess, J. (2017). Machine learning: An applied econometric approach. *Journal of Economic Perspectives*, 31(2), 87–106. <https://doi.org/10.1257/jep.31.2.87>
2. Varian, H. R. (2014). Big data: New tricks for econometrics. *Journal of Economic Perspectives*, 28(2), 3–28. <https://doi.org/10.1257/jep.28.2.3>
3. Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, 349(6245), 255–260. <https://doi.org/10.1126/science.aaa8415>
4. Kelleher, J. D., Mac Namee, B., & D'Arcy, A. (2015). *Fundamentals of machine learning for predictive data analytics: Algorithms, worked examples, and case studies*. MIT Press.
5. Edelmann, A., Wolff, T., Montagne, D., & Bail, C. A. (2020). Computational social science and sociology. *Annual Review of Sociology*, 46, 61–81. <https://doi.org/10.1146/annurev-soc-121919-054621>
6. Mullainathan, S., & Spiess, J. (2017). Machine learning for social science: An agnostic approach. *Annual Review of Economics*, 9, 685–725. <https://doi.org/10.1146/annurev-economics-080315-015427>
7. Hofman, J. M., Watts, D. J., Athey, S., et al. (2021). Integrating explanation and prediction in computational social science. *Nature*, 595, 181–188. <https://doi.org/10.1038/s41586-021-03659-0>
8. Chen, Y., Wu, X., Hu, A., He, G., & Ju, G. (2021). Social prediction: A new research paradigm based on machine learning. *Journal of Chinese Sociology*, 8, Article 15. <https://doi.org/10.1186/s40711-021-00152-z>
9. Di Franco, G., & Santurro, M. (2021). Machine learning, artificial neural networks and social research. *Quality & Quantity*, 55, 1007–1025. <https://doi.org/10.1007/s11135-020-01037-y>
10. Peres, R. S., Jia, X., Lee, J., Sun, K., Colombo, A. W., & Barata, J. (2020). Industrial artificial intelligence in Industry 4.0—Systematic review, challenges and outlook. *IEEE Access*, 8, 220121–220139. <https://doi.org/10.1109/ACCESS.2020.3042874>
11. Carvalho, T. P., Soares, F. A. A. M. N., Vita, R., Francisco, R. P., Basto, J. P., & Alcalá, S. G. S. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. *Computers & Industrial Engineering*, 137, 106024. <https://doi.org/10.1016/j.cie.2019.106024>
12. Nguyen, K. T. P., & Medjaher, K. (2019). A new dynamic predictive maintenance framework using deep learning for failure prognostics. *Reliability Engineering & System Safety*, 188, 251–262. <https://doi.org/10.1016/j.ress.2019.03.018>

13. Ayvaz, S., & Alpay, K. (2021). Predictive maintenance system for production lines in manufacturing: A machine learning approach using IoT data in real-time. *Expert Systems with Applications*, 173, 114598. <https://doi.org/10.1016/j.eswa.2021.114598>
14. Lee, J., Wu, F., Zhao, W., Ghaffari, M., Liao, L., & Siegel, D. (2014). Prognostics and health management design for rotary machinery systems—Reviews, methodology and applications. *Mechanical Systems and Signal Processing*, 42(1–2), 314–334. <https://doi.org/10.1016/j.ymssp.2013.06.004>
15. Susto, G. A., Schirru, A., Pampuri, S., McLoone, S., & Beghi, A. (2015). Machine learning for predictive maintenance: A multiple classifier approach. *IEEE Transactions on Industrial Informatics*, 11(3), 812–820. <https://doi.org/10.1109/TII.2014.2349359>
16. Wuest, T., Weimer, D., Irgens, C., & Thoben, K.-D. (2016). Machine learning in manufacturing: Advantages, challenges, and applications. *Production & Manufacturing Research*, 4(1), 23–45. <https://doi.org/10.1080/21693277.2016.1192517>
17. Lei, Y., Li, N., Guo, L., Li, N., Yan, T., & Lin, J. (2018). Intelligent fault diagnosis and remaining useful life prediction of machinery using deep learning: A review. *Measurement*, 130, 1–15. <https://doi.org/10.1016/j.measurement.2018.07.004>
18. Carvalho, T. P., Soares, F. A. A. M. N., de Souza, B. F., Vita, R., Francisco, R. P., Basto, J. P., & Alcalá, S. G. S. (2020). A systematic literature review of artificial intelligence in predictive maintenance. *Computers & Industrial Engineering*, 137, 106024.
19. van der Aalst, W. M. P. (2016). *Process mining: Data science in action* (2nd ed.). Springer. <https://doi.org/10.1007/978-3-662-49851-4>
20. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521, 436–444. <https://doi.org/10.1038/nature14539>