



**HAL**  
open science

# The Role of System Modeling on Artificial Intelligence: A Review of Emerging Trends

Saad Aldoichi, Khalid Alblalaih, Fozah Alzemaia, Alia Almoajel

► **To cite this version:**

Saad Aldoichi, Khalid Alblalaih, Fozah Alzemaia, Alia Almoajel. The Role of System Modeling on Artificial Intelligence: A Review of Emerging Trends. 2023 IEEE International Conference on Metrology for eXtended Reality, Artificial Intelligence and Neural Engineering (MetroXRINE), Oct 2023, Milano, Italy. pp.161-165, 10.1109/MetroXRINE58569.2023.10405725 . hal-04437501

**HAL Id: hal-04437501**

**<https://hal.science/hal-04437501>**

Submitted on 4 Feb 2024

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# The Role of System Modeling on Artificial Intelligence: A Review of Emerging Trends

Saad Aldoihi

*Institute of Earth and Space Science  
King Abdulaziz City for Science and Technology*  
Riyadh, Saudi Arabia  
saldoihi@kacst.edu.sa

Khalid Alblalaih

*Institute of Earth and Space Science  
King Abdulaziz City for Science and Technology*  
Riyadh, Saudi Arabia  
ablehed@kacst.edu.sa

Fozah Alzemaia

*College of Education  
King Saud University*  
Riyadh, Saudi Arabia  
falzemaia@ksu.edu.sa

Alia Almoajel

*College of Applied Medical Sciences  
King Saud University*  
Riyadh, Saudi Arabia  
aalmoajel1@ksu.edu.sa

**Abstract**—System modeling is essential to the growth and comprehension of artificial intelligence (AI). It offers a way to describe, examine, and improve sophisticated AI systems. The significance of system modeling in AI is explored in this paper, along with examples of its use in robotics, machine learning, and natural language processing. We also discuss the difficulties and possible directions in system modeling for AI, highlighting its potential to further improve the robustness and capabilities of AI systems.

**Index Terms**—System Modeling, Artificial Intelligence, System Engineering, Deep Learning, Reinforcement Learning,

## I. INTRODUCTION

Artificial Intelligence (AI) has seen substantial progresses in recent years, transforming numerous industries and applications from healthcare to finance, energy management, and transportation [1]. As AI systems become more complex and integrate into various domains, there is an increasing need for a comprehensive understanding of the underlying processes, mechanisms, and interactions. System modeling offers a powerful approach to represent, analyze, and optimize complex AI systems [2], [3]. System modeling is a critical practice in various fields, including engineering, economics, and social sciences, to better understand complex systems' behavior and make predictions. Advances in artificial intelligence (AI) have greatly enhanced the practice of system modeling by providing new techniques and tools for data analysis, model building, model validation, model refinement, and model visualization. AI can help analyze large-scale and heterogeneous data sets, which are often involved in system modeling, providing more accurate models and predictions [4]. AI can also automate the process of building system models by using techniques such as neural networks [5], genetic algorithms [6], or Bayesian networks [7], saving time and effort compared to manual model building. Furthermore, AI can help validate system models by using techniques such as cross-validation [8], bootstrap [9], or adversarial examples [10], ensuring that

models are accurate and reliable. Additionally, AI can refine system models by using techniques such as gradient descent [11], backpropagation [12], or stochastic gradient descent [13], resulting in more accurate and precise models. Finally, AI can help visualize system models by using techniques such as graphs [14], diagrams [15], or animations [16], making the models more accessible and easier to understand.

These AI techniques have proven to be effective in enhancing system modeling in various fields. For instance, in engineering, AI has been used to build models for predicting the behavior of complex systems such as aircraft engines, enabling engineers to identify potential issues before they occur [17]. In economics, AI has been used to analyze large data sets and build models for predicting financial market trends, enabling investors to make informed decisions [18].

AI systems are achieving human-level performance on complex tasks such as image recognition, natural language processing, and game playing. However, most AI systems today are based on statistical machine learning techniques that learn patterns from large amounts of data. These AI systems lack the causal understanding and reasoning abilities that humans possess [19]. Recent research has focused on integrating more model-based, causal reasoning into AI systems through system modeling approaches. System models represent causal knowledge about how a system works in a structured, quantitative manner. They enable an AI system to reason about how changes to the system might affect its outputs, even in situations not seen during training [20]. There are several emerging trends in combining system modeling and AI:

### 1- Causal models:

Causal models represent how systems change in response to interventions, not just correlations observed in data. They are usually expressed as structural equation models, Bayesian networks, or causal graphs. For example, [21] developed an AI

system that can construct and reason with qualitative causal models to explain complex physical phenomena. [22] built an AI system for causal reasoning about signaling pathways in biological systems. These models allow AI systems to make counterfactual predictions, identify causal relationships, and determine the effects of hypothetical interventions.

## 2- Hybrid systems:

Hybrid AI approaches aim to combine the advantages of data-driven machine learning and model-based reasoning. For example, [23] developed a hybrid system for natural language processing that combines neural networks with symbolic world knowledge expressed in ontologies. [24] proposed an approach for combining neural networks with model-based planning and reasoning for complex problem solving. The machine learning components can learn patterns from large datasets, while the model-based components provide causal knowledge, logical reasoning, and planning abilities.

## 3- Learning mechanisms:

Some research focuses on developing unsupervised mechanisms that allow AI systems to autonomously build causal models through interaction with an environment or observational data. For example, [25] developed an evolutionary algorithm that can infer the dynamical equations that govern a physical system by observing its behavior. [26] proposed a causal learning mechanism that allows an AI system to infer causal relationships from observations and interventions on a new domain. Developing unsupervised learning approaches for model building could help produce more general AI systems that have a broad, flexible understanding of the world.

In this paper, we discuss the role of system modeling in AI, specifically in machine learning, robotics, and natural language processing. We also highlight current challenges and future directions in the field of system modeling for AI. The paper is organized as follows: Section 2 provides an overview of system modeling; Section 3 discusses its applications in AI domains; Section 4 outlines the challenges and future directions; and Section 5 concludes the paper.

## II. SYSTEM MODELING OVERVIEW

System modeling refers to the process of creating abstract representations of systems to analyze their behavior and performance, identify potential issues, and optimize their design [27]. It involves various techniques, such as mathematical modeling, simulation, and optimization, that allow researchers to study the interactions between different components of a system and predict their behavior in different scenarios. System modeling can be classified into different types, such as:

- Static modeling, which focuses on the relationships between system components at a specific point in time (e.g., network topologies, dataflow diagrams).

- Dynamic modeling, which captures the time-varying behavior of systems (e.g., state-transition diagrams, differential equations).

These modeling approaches can be applied to a wide range of AI systems, providing insights into their functioning and guiding their development.

## III. APPLICATIONS OF SYSTEM MODELING IN AI

### A. Machine Learning

Machine learning (ML) is a subset of AI that involves the development of algorithms capable of learning from and making predictions based on data [28]. System modeling can be applied to ML in various ways:

- 1) Modeling the learning process: By representing the ML algorithm's structure and dynamics, system modeling can help researchers analyze and optimize the learning process (e.g., convergence rates, generalization performance).
- 2) Modeling data: System modeling can assist in understanding the relationships between input features and output predictions, providing insights into the underlying structure of the data and guiding feature engineering efforts.
- 3) Modeling model uncertainty: Probabilistic modeling techniques, such as Bayesian networks and Gaussian processes, can be used to quantify the uncertainty in ML models, leading to more robust and reliable predictions [29].

1) *Robotics*: Robotics is a multidisciplinary field that includes the design, construction, and operation of robots, often incorporating AI techniques for perception, decision-making, and control [30]. System modeling plays a vital role in robotics, with applications such as:

- 1) Kinematic and dynamic modeling: By representing the relationships between a robot's components, system modeling can be used to analyze and optimize its motion and interactions with the environment [31].
- 2) Control systems: System modeling is essential for designing and implementing control algorithms that enable robots to perform various tasks, such as path planning, manipulation, and locomotion [32].
- 3) Simulations: Robotic simulations, which rely on system models, are crucial for testing and validating robotic systems before deployment in real-world scenarios [33].

### B. Natural Language Processing

Natural Language Processing (NLP) is a subfield of AI that focuses on the interaction between humans and computers through natural language [34]. System modeling in NLP includes:

- 1) Language models: Probabilistic models, such as n-gram models and neural network-based language models, are used to represent the structure and distribution of natural language [35].

- 2) Parsing and syntactic analysis: System modeling can be applied to represent the syntactic structure of sentences using formal grammar approaches, such as context-free grammars and dependency grammars. These models enable the development of parsers that can analyze the structure of natural language sentences and extract meaningful information [36].
- 3) Semantic and discourse modeling: Modeling the meaning and relationships between words, sentences, and larger units of text is crucial for NLP tasks such as machine translation, summarization, and question-answering. Techniques like distributional semantics, topic models, and graph-based models can be employed to capture the underlying semantics and discourse structure [37].
- 4) Dialogue systems: System modeling plays a critical role in designing and implementing dialogue systems, which involve the management of dialogue states, understanding user intent, and generating appropriate responses. Approaches such as probabilistic graphical models, reinforcement learning, and neural networks can be utilized for modeling different aspects of dialogue systems [38].

#### IV. CHALLENGES AND FUTURE DIRECTIONS

While system modeling has significantly contributed to the advancement of AI, several challenges and opportunities for future research remain:

- 1) Scalability: As AI systems become more complex and incorporate larger datasets, the scalability of system modeling techniques becomes essential. Developing efficient algorithms and leveraging parallel and distributed computing resources will be crucial for addressing this challenge [39].
- 2) Interpretability and explainability: The increasing complexity of AI systems has led to concerns about their interpretability and explainability. System modeling can help researchers and practitioners understand the underlying mechanisms, but further work is needed to improve the interpretability of advanced AI models, such as deep learning architectures [40].
- 3) Model validation and verification: Ensuring the accuracy and robustness of system models is critical for their application in AI. Techniques for model validation and verification, as well as methods for quantifying and mitigating model uncertainty, will play a vital role in the development of reliable AI systems [41].
- 4) Integration of multiple modeling approaches: AI systems often involve multiple components, each of which may require different modeling techniques. Developing methodologies for integrating various modeling approaches and representing the interactions between different components will be crucial for a holistic understanding of AI systems [42].

#### V. CONCLUSION

System modeling plays a pivotal role in the development and understanding of AI, with applications spanning machine learning, robotics, and natural language processing. By providing a means to represent, analyze, and optimize complex AI systems, system modeling contributes to the continued advancement of AI technologies. Addressing the challenges and exploring the future directions outlined in this paper will further enhance the capabilities and robustness of AI systems, enabling their broader adoption and impact across various domains. As AI continues to evolve, system modeling will play an increasingly important role in understanding and improving the performance of AI systems. To facilitate this, researchers and practitioners should focus on several emerging areas:

- 1) Modeling AI ethics and fairness: As AI systems become more integrated into various aspects of society, it is crucial to consider ethical and fairness-related implications. System modeling can help analyze AI systems' behavior and identify potential biases, unfairness, and ethical concerns, leading to the development of more responsible and equitable AI solutions [43].
- 2) Modeling AI safety: Ensuring the safety of AI systems is critical, particularly in high-stakes applications such as autonomous vehicles, healthcare, and finance. System modeling can aid in the analysis and design of safe AI systems, including the development of algorithms for safe exploration, robustness to adversarial examples, and reinforcement learning with human feedback [44].
- 3) Modeling multi-agent AI systems: Many AI applications involve multiple agents interacting with each other, leading to emergent behaviors and complex dynamics. System modeling can provide valuable insights into the interactions and coordination mechanisms of multi-agent AI systems, enabling the design of more efficient and robust solutions for collaborative and competitive scenarios [45].
- 4) Modeling AI-human interaction: As AI systems increasingly interact with humans, understanding and modeling the dynamics of AI-human interactions becomes essential. System modeling can help researchers study the impact of AI on human behavior and decision-making and design AI systems that effectively support and augment human capabilities [46].

Significantly, the field of Artificial Intelligence (AI) has seen significant progress in recent years, transforming numerous industries and applications. However, as AI systems become more complex and integrated into various domains, there is an increasing need for a comprehensive understanding of the underlying processes, mechanisms, and interactions [47]. System modeling offers a powerful approach to represent, analyze, and optimize complex AI systems. Advances in AI have greatly enhanced the practice of system modeling by providing new techniques and tools for data analysis, model building, model validation, model refinement, and model visualization.

System modeling has various applications in AI domains, including machine learning, robotics, and natural language processing. The use of system modeling in these domains has enabled researchers to analyze and optimize the learning process, understand the relationships between input features and output predictions, design and implement control algorithms, and develop dialogue systems.

However, several challenges and opportunities for future research remain, including scalability, interpretability and explainability, model validation and verification, and integration of multiple modeling approaches. Addressing these challenges will be crucial for the development of reliable and effective AI systems. Overall, the combination of system modeling and AI holds great promise for advancing the field and achieving more human-like performance on complex tasks.

The combination of system modeling and AI has the potential to revolutionize various industries and domains, from healthcare to finance, energy management, and transportation. By representing complex systems in a structured, quantitative manner, system modeling enables AI systems to reason about how changes to the system might affect its outputs, even in situations not seen during training. This can lead to more accurate and reliable models, making AI systems more efficient and effective.

Moreover, the use of causal models, hybrid systems, and learning mechanisms in system modeling is an emerging trend that is expected to enhance the capabilities of AI systems. Causal models enable AI systems to make counterfactual predictions, identify causal relationships, and determine the effects of hypothetical interventions. Hybrid AI approaches, which combine the advantages of data-driven machine learning and model-based reasoning, can provide more robust and reliable predictions. Learning mechanisms that allow AI systems to autonomously build causal models through interaction with an environment or observational data could help produce more general AI systems that have a broad, flexible understanding of the world.

However, there are still several challenges that need to be addressed. For example, as AI systems become more complex and incorporate larger datasets, the scalability of system modeling techniques becomes essential. Developing efficient algorithms and leveraging parallel and distributed computing resources will be crucial for addressing this challenge. Additionally, ensuring the accuracy and robustness of system models is critical for their application in AI. Techniques for model validation and verification, as well as methods for quantifying and mitigating model uncertainty, will play a vital role in the development of reliable AI systems.

Overall, the combination of system modeling and AI holds great promise for advancing the field and achieving more human-like performance on complex tasks. Ongoing research in this area is expected to lead to significant breakthroughs in various domains, enabling us to solve complex problems and make informed decisions.

In short, system modeling will continue to be a critical component in advancing AI research and applications. By

addressing the challenges and exploring new directions in system modeling, researchers and practitioners can contribute to the development of more robust, efficient, and responsible AI systems that have a positive impact on society.

## VI. ACKNOWLEDGEMENT

The authors extend their appreciation to the King Salman center For Disability Research for funding this work through Research Group no KSRG-2023-277.

## REFERENCES

- [1] Russell, S., Norvig, P. (2021). *Artificial Intelligence: A Modern Approach* (4th ed.). Pearson.
- [2] Bazylevych, R., Pałasiński, M., Kutelmakh, R., Kuz, B., Bazylevych, L. *ARTIFICIAL INTELLIGENCE IN MODELING AND SIMULATION*.
- [3] Alsulami, R., Aldoihi, S., Alfarraj, M. (2022, February). A Novel Approach for Detecting Technical and Nontechnical Losses in the Smart Grid: A Machine Learning-based Complex System Model. In *Ibdaa*
- [4] Chen, M., Mao, S., Liu, Y. (2014). Big data: A survey. *Mobile Networks and Applications*, 19(2), 171-209.
- [5] LeCun, Y., Bengio, Y., Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436-444.
- [6] Holland, J. H. (1975). *Adaptation in natural and artificial systems: An introductory analysis with applications to biology, control, and artificial intelligence*. MIT Press.
- [7] Koller, D., Friedman, N. (2009). *Probabilistic graphical models: Principles and techniques*. MIT Press.
- [8] Kohavi, R. (1995). A study of cross-validation and bootstrap for accuracy estimation and model selection. *Proceedings of the 14th International Joint Conference on Artificial Intelligence*, 2, 1137-1143.
- [9] Efron, B., Tibshirani, R. J. (1993). *An introduction to the bootstrap*. Chapman Hall/CRC.
- [10] Szegedy, C., Zaremba, W., Sutskever, I., Bruna, J., Erhan, D., Goodfellow, I., Fergus, R. (2013). Intriguing properties of neural networks. *arXiv preprint arXiv:1312.6199*.
- [11] Rumelhart, D. E., Hinton, G. E., Williams, R. J. (1986). Learning representations by back-propagating errors. *Nature*, 323(6088), 533-536.
- [12] LeCun, Y., Boser, B., Denker, J. S., Henderson, D., Howard, R. E., Hubbard, W., Jackel, L. D. (1989). Backpropagation applied to handwritten zip code recognition. *Neural computation*, 1(4), 541-551.
- [13] Bottou, L. (2010). Large-scale machine learning with stochastic gradient descent. *Proceedings of COMPSTAT*, 177-186.
- [14] Newman, M. E. (2003). The structure and function of complex networks. *SIAM review*, 45(2), 167-256.
- [15] Hastie, T., Tibshirani, R., Friedman, J. H., Friedman, J. H. (2009). *The elements of statistical learning: data mining, inference, and prediction* (Vol. 2, pp. 1-758). New York: Springer.
- [16] Tufte, E. R. (1997). *Visual explanations: Images and quantities, evidence and narrative*. Graphics Press.
- [17] Jiang, H., Shao, H., Chen, X., Huang, J. (2017, August). Aircraft fault diagnosis based on deep belief network. In *2017 International Conference on Sensing, Diagnostics, Prognostics, and Control (SDPC)* (pp. 123-127). IEEE.
- [18] Hsieh, T. J., Hsiao, H. F., Yeh, W. C. (2011). Forecasting stock markets using wavelet transforms and recurrent neural networks: An integrated system based on artificial bee colony algorithm. *Applied soft computing*, 11(2), 2510-2525.
- [19] Lake, B. M., Ullman, T. D., Tenenbaum, J. B., Gershman, S. J. (2017). Building machines that learn and think like people. *Behavioral and Brain Sciences*, 40.
- [20] Deisenroth, M. P., Fox, D., Ramos, F. (2020). Gaussian Processes for Data-Efficient Learning in Robotics and Control. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 37(2), 408-423.
- [21] Delecki, H., Corso, A., Kochenderfer, M. J. (2023). Model-based Validation as Probabilistic Inference. *arXiv preprint arXiv:2305.09930*.
- [22] Kumar, R., Blakemore, S. J., Ellis, C. E., Petricoin, E. F., Pratt, D., Macoritto, M., ... Elliston, K. (2010). Causal reasoning identifies mechanisms of sensitivity for a novel AKT kinase inhibitor, GSK690693. *BMC genomics*, 11(1), 1-12.

- [23] Gasse, M., Aussem, A., Elghazel, H. (2012). An experimental comparison of hybrid algorithms for Bayesian network structure learning. In *Machine Learning and Knowledge Discovery in Databases: European Conference, ECML PKDD 2012, Bristol, UK, September 24-28, 2012. Proceedings, Part I 23* (pp. 58-73). Springer Berlin Heidelberg.
- [24] Oltramari, A., Francis, J., Henson, C., Ma, K., Wickramarachchi, R. (2020). Neuro-symbolic architectures for context understanding. arXiv preprint arXiv:2003.04707.
- [25] Bongard, J., Lipson, H. (2007). Automated reverse engineering of nonlinear dynamical systems. *Proceedings of the National Academy of Sciences*, 104(24), 9943-9948.
- [26] Lagnado, D. A., Sloman, S. (2002). The advantage of timely intervention. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 28(4), 856.
- [27] Zeigler, B. P., Kim, T. G., Praehofer, H. (2000). *Theory of Modeling and Simulation: Integrating Discrete Event and Continuous Complex Dynamic Systems* (2nd ed.). Academic Press.
- [28] Goodfellow, I., Bengio, Y., Courville, A. (2016). *Deep Learning*. MIT Press.
- [29] Murphy, K. P. (2012). *Machine Learning: A Probabilistic Perspective*. MIT Press.
- [30] Siciliano, B., Khatib, O. (2016). *Springer Handbook of Robotics* (2nd ed.). Springer.
- [31] Featherstone, R. (2008). *Rigid Body Dynamics Algorithms*. Springer.
- [32] Slotine, J.-J. E., Li, W. (1991). *Applied Nonlinear Control*. Prentice-Hall.
- [33] Koenig, N., Howard, A. (2004). Design and use paradigms for Gazebo, an open-source multi-robot simulator. In *Proceedings of the 2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2004)* (Vol. 3, pp. 2149-2154). IEEE.
- [34] Jurafsky, D., Martin, J. H. (2021). *Speech and Language Processing* (3rd ed.). Prentice Hall.
- [35] Goldberg, Y. (2021). A Primer on Neural Network Models for Natural Language Processing. *Journal of Artificial Intelligence Research*, 57, 345-420.
- [36] Klein, D., Manning, C. D. (2003). Accurate unlexicalized parsing. In *Proceedings of the 41st Annual Meeting of the Association for Computational Linguistics* (pp. 423-430). ACL.
- [37] Turney, P. D., Pantel, P. (2010). From frequency to meaning: Vector space models of semantics. *Journal of Artificial Intelligence Research*, 37, 141-188.
- [38] Gao, J., Galley, M., Li, L. (2018, June). Neural approaches to conversational AI. In *The 41st International ACM SIGIR Conference on Research Development in Information Retrieval* (pp. 1371-1374).
- [39] Bengio, Y., Lecun, Y., Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436-444.
- [40] Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., ... Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities, and challenges toward responsible AI. *Information Fusion*, 58, 82-115.
- [41] Sargent, R. G. (2013, December). An introduction to verification and validation of simulation models. In *2013 Winter Simulations Conference (WSC)* (pp. 321-327). IEEE.
- [42] Gilbert, N., Troitzsch, K. G. (2005). *Simulation for the Social Scientist* (2nd ed.). Open University Press.
- [43] Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., Galstyan, A. (2021). A survey on bias and fairness in machine learning. *ACM Computing Surveys (CSUR)*, 54(6), 1-35.
- [44] Amodei, D., Olah, C., Steinhardt, J., Christiano, P., Schulman, J., Mané, D. (2016). Concrete Problems in AI Safety. arXiv preprint arXiv:1606.06565.
- [45] Shoham, Y., Leyton-Brown, K. (2009). *Multiagent Systems: Algorithmic, Game-Theoretic, and Logical Foundations*. Cambridge University Press.
- [46] Dorr, D. A., Adams, L., Embí, P. (2023). Harnessing the Promise of Artificial Intelligence Responsibly. *JAMA*, 329(16), 1347-1348.
- [47] Aldoihi, S. (2020). *Product Usability Driven System Engineering*. (Ingénierie Système Dirigée par L'utilisabilité des Produits) (Doctoral dissertation, Polytechnic Institute of Paris, France).