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A Hybrid Explainable AI and Deep Learning Framework for Intelligent Decision Support in Smart Digital Ecosystems

Abstract
The increasing complexity of smart digital ecosystems has accelerated the adoption of artificial intelligence (AI)-driven decision support systems capable of processing large-scale, heterogeneous data for intelligent and timely decision-making. Among contemporary AI technologies, deep learning has demonstrated exceptional predictive capabilities; however, its limited interpretability has raised concerns regarding transparency, trust, and accountability in critical decision environments. Explainable Artificial Intelligence (XAI) has emerged as a promising solution to address these limitations by providing meaningful insights into model behavior while preserving predictive performance. This narrative review critically examines the convergence of deep learning and XAI in the development of hybrid intelligent decision support frameworks for smart digital ecosystems. The review synthesizes recent advances in intelligent decision support systems, deep learning architectures, explainability techniques, hybrid XAI–deep learning models, and their applications across healthcare, manufacturing, finance, transportation, smart cities, and the Industrial Internet of Things. It further discusses emerging technologies, including digital twins, federated learning, and multimodal AI, that are reshaping explainable decision intelligence. In addition, the review identifies key challenges related to scalability, computational complexity, privacy, fairness, ethical governance, and standardized explainability evaluation. The findings indicate that hybrid XAI–deep learning frameworks significantly improve transparency, user trust, and decision reliability while maintaining high analytical performance. This review provides a comprehensive perspective on current developments and highlights future research directions for building trustworthy, scalable, and human-centric intelligent decision support systems in next-generation smart digital ecosystems.

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INTRODUCTION

Artificial Intelligence (AI) has ushered the smart digital ecosystem into a new era of interconnection that enables intelligent and data-led decisions in various fields. These ecosystems support seamless communication, sharing of resources, and autonomous operation through their integration of technologies like the Internet of Things (IoT), cloud computing, big data analytics, edge computing, and cyber-physical systems. With the growth of digital data in size and complexity, the need to use Intelligent Decision Support Systems (IDSS) to derive actionable intelligence for strategic and operational decision making is growing. AI has emerged as the cornerstone of these systems, bolstering these analytical capabilities, adaptability, and organizational efficiency, which are far more than what can be achieved with traditional rule-based systems (Jacobides et al., 2021; Beshley et al., 2024).

The use of deep learning has become one of the most important contributions to intelligent decisions, support for their ability to learn complex patterns from high-dimensional data. However, advanced architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), transformers, and deep reinforcement learning (DRL) models have played a significant role in enhancing the predictive capabilities of AI systems in various domains, including healthcare, finance, cybersecurity, manufacturing, and smart cities. They can automate complex decision-making processes, making deep learning a critical technology in today's digital ecosystem (Taherdoost, 2023; Shuford, 2024).

However, the black-box effect of deep learning models, which means they are not transparent or easily explained to users, poses a challenge in maintaining trust and transparency, especially in high-stakes scenarios where decisions need to be interpretable and explainable. Explainable Artificial Intelligence (XAI) is a solution to this problem that gives understandable explanations of the results produced by Artificial Intelligence while maintaining the predictive power. When integrated with deep learning, hybrid frameworks provide a more transparent approach to model analytics, improve regulatory compliance, mitigate bias, and foster effective collaboration between human and machine decision-making processes, ensuring the reliability and trustworthiness of intelligent decision support (Jain et al., 2025; Fatima et al., 2025).

Despite the large volume of research on AI, Deep Learning and XAI, there is a lack of integration of these in a smart digital ecosystem for intelligent decision support. Accordingly, this review compiles the recent developments in the hybrid Explainable AI and Deep Learning frameworks, considers their applications, outlines current obstacles, and points out future research avenues for the creation of intelligently supported decision-making systems that are transparent, robust, and human-centric (Duan et al., 2019; Mijwil et al., 2022).

Review Objectives

1.To review the role of Explainable AI and deep learning in intelligent decision support for smart digital ecosystems.

2.To analyze hybrid Explainable AI–deep learning frameworks and their applications across diverse domains.

3.To identify key challenges, research gaps, and future directions for trustworthy intelligent decision support systems.

2. FOUNDATIONS OF INTELLIGENT DECISION SUPPORT IN SMART DIGITAL ECOSYSTEMS

Intelligent decision support systems (IDSS) are continually developing digital technologies and computational intelligence. Traditional Decision Support Systems (DSS) were mainly developed to support managers in structured and semi-structured decision making within databases and statistical models and by rule-based methods. They are effective in processing historical information but had limited adaptability to dynamic and complex environments. Artificial Intelligence, Machine Learning, and sophisticated analytics have given rise to smart DSS systems that learn from data, make predictive decisions, and can make autonomous decisions. This change has led to a better speed, precision, and versatility of decision-making in multiple application areas (Sànchez-Marrè, 2022a, 2022b).

This has been further fueled by the advent of smart digital ecosystems, which have developed into interconnected environments where organisations, smart devices, cloud platforms and users interact and continuously share data and knowledge. They bring together technologies like the Internet of Things (IoT), Cloud Computing, Edge Computing, and Artificial Intelligence (AI) to facilitate real-time collaboration, adaptive operations, and intelligent service delivery. They are highly connected and offer ease of interoperability, and enable the data-driven decision processes needed to react to the dynamic operational conditions. Therefore, smart digital ecosystems have emerged as the technological backbone of smart decision support systems of the next generation (Rodriguez-Garcia et al., 2023; Ocampo et al., 2025).

In such ecosystems, AI serves as the backbone of decision intelligence, converting vast amounts of complex, multidimensional data into valuable insight for decision-making, forecasting, optimization, and pattern recognition. Modern intelligent decision support systems are characterized by continuous learning, scalability, interoperability, transparency and human centred intelligence and can support organizations in making timely, confident, evidence-based decisions. Furthermore, the fusion of AI and digital ecosystem technologies has boosted innovation, operational resilience, and strategic decision-making, as well as enabled trustworthy collaboration between humans and intelligent systems. These breakthroughs make intelligent decision support a key element of future digital transformation efforts in smart environments such as healthcare, manufacturing, finance, transportation, and others (Maddukuri, 2023; Mygal et al., 2021; Secundo et al., 2025). Table 1 shows the evolution of decision support systems, from the traditional rule-based systems to explainable AI-based intelligent ecosystems, along with the technological development and the scope of decision making increased with each generation.

Table 1. Evolution of Intelligent Decision Support Systems

Stage	Core Technologies	Key Characteristics	Reference
Traditional DSS	Databases, Rule-based Systems	Structured decision support and reporting	Sànchez-Marrè (2022a)
Intelligent DSS	Machine Learning, Knowledge-Based Systems	Predictive analytics and adaptive learning	Sànchez-Marrè (2022b)
AI-Driven DSS	Artificial Intelligence, Automation	Autonomous and data-driven decision-making	Maddukuri (2023)
Smart Digital Ecosystems	AI, IoT, Cloud, Edge Computing	Real-time, connected, and collaborative decisions	Rodriguez-Garcia et al. (2023); Ocampo et al. (2025)
Hybrid Explainable AI DSS	Deep Learning, Explainable AI	Transparent, trustworthy, and human-centric decision support	Secundo et al. (2025)

3. DEEP LEARNING TECHNOLOGIES FOR INTELLIGENT DECISION SUPPORT

This has made deep learning a crucial component of intelligent decision support systems, as it allows for the automatic extraction and high accuracy prediction from complex data with high dimensions. Deep learning models, unlike traditional machine learning methods, are able to learn hierarchical representations, thus enhancing the quality of the decisions in various fields including healthcare, finance, manufacturing, cybersecurity, and smart cities. These technologies are based on Deep Neural Networks (DNNs) that model complex nonlinear relationships, and Convolutional Neural Networks (CNNs) that are very successful in the analysis of image and spatial data, such as visual inspection and medical imaging. Recurrent Neural Networks (RNNs) in general, and Long Short-Term Memory (LSTMs) in particular, excel at modelling sequences and can be effectively used for forecasting time series data, speech recognition, and predictive decision making (Cichy & Kaiser, 2019; Yu et al., 2019).

Transformer-based architecture has also brought a new level of sophistication to intelligent decision-making, particularly in understanding long-range contextual relationships, which is more effective than traditional sequential models. These architectures have transformed NLP applications and are being used in more and more multimodal decision-making scenarios that involve text, images, and structured data. More recently, foundation models such as Large Language Models (LLMs) and Large Multimodal Models (LMMs) have shown amazing generalization capabilities by being pre-trained at scale and transfered to a variety of tasks. They have been successful in performing multiple analytical tasks without significant task-specific adaptation, which has facilitated intelligent decision support in research, industry, and public services (Gillioz et al., 2020; Chen et al., 2024).

Deep learning has significantly improved the ability of intelligent decision support systems to provide precise, scalable, data-driven recommendations due to its continuous evolution. However, these models are demanding in terms of computational power, large-annotated data sets and are time consuming to train. They are also less interpretable and prone to bias which makes them challenging in high-stakes decision setting. This has led to the growing significance of combining deep learning with explainable AI (XAI) to design and create interpretable, trustworthy, and human-centered decision-making support tools that achieve strong prediction accuracy while maintaining interpretability (Sharifani & Amini, 2023; Gadhave et al., 2025). Figure 1 shows the key deep learning technologies that support intelligent decision support systems, ranging from deep neural networks to transformer architectures to foundation models for next-generation decision intelligence.

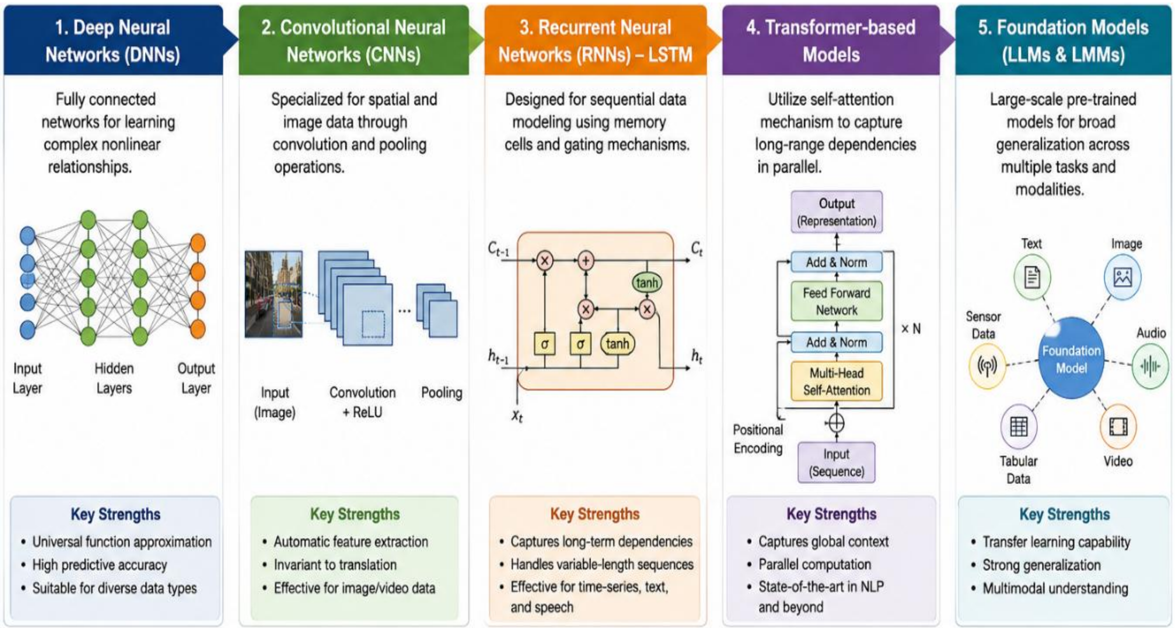

Figure 1. Major Deep Learning Architectures for Intelligent Decision Support Systems

4. EXPLAINABLE ARTIFICIAL INTELLIGENCE FOR TRUSTWORTHY DECISION MAKING

Explainable Artificial Intelligence (XAI) is becoming a key paradigm to enhance the transparency, interpretability and trustworthiness of intelligent decision support systems. Even though deep learning models offer exceptional predictive accuracy, they are general systems that operate as "black boxes" and are hard for users to grasp how automated decisions are made. To overcome this challenge, XAI is developed to provide explications that are interpretable by humans and are able to increase the transparency of the models, assist in bias detection, help in regulatory compliance, and boost the users' trust in AI-driven decision-making. For this reason, explainability has emerged as a critical stakeholder in many critical areas including healthcare, finance, cybersecurity, and autonomous systems (Chamola et al., 2023; Ali et al., 2023).

Explanation techniques normally can be divided into two types: global and local. Global explainability gives an overarching overview of the model behavior by identifying the relationships learnt over the entire data set whilst local explainability explains individual predictions. In addition, there are two types of XAI methods: model-specific and model-agnostic. Model-specific techniques are tailored to specific algorithms and are usually based on their internal architecture to provide explanations, whereas model-agnostic approaches are able to interpret the predictions of almost any machine learning or deep learning model, showing flexibility in different applications (Angelov et al., 2021; Devireddy, 2025).

SHAP (Shapley Additive Explanations) is one of the most popular methods of contemporary XAI, which quantifies the importance of each feature in a prediction based on cooperative game theory, and gives mathematically sound and consistent explanations. LIME (Local Interpretable Model-Agnostic Explanations) generates simpler local surrogate models that approximate more complicated models to explain their predictions on a one-by-one basis. In the context of transformer and deep learning models, attention-based explainability has been emphasized for its ability to identify the region of the input space that most influences the output of the model, which helps the models to be easier to interpret in a real application, e.g., in healthcare and natural language processing (Ali et al., 2023; Amjad et al., 2023).

Explainability has been extended with counterfactual and causal explanations in recent research. Causal explainability is focused on discovering cause and effect relationships and not just statistical relationships, whereas counterfactual methods aim to provide insights for the user on how little needs to change in the model to change its prediction. Such methods enhance the comprehensibility and applicability of AI explanations and contribute to better human decision-making. Explainability should be assessed by the following criteria to guarantee the reliability of XAI systems: fidelity, interpretability, robustness, stability, fairness and computational efficiency. These techniques collectively make EAI a key aspect of trustworthy intelligent decision support systems in smart digital ecosystems (Chamola et al., 2023; Angelov et al., 2021). Table 2 presents a comparison of the major EAI techniques in terms of their type of explainability, key strengths and representative application areas, illustrating complementary ways to build trustworthy intelligent decision support systems.

Table 2. Comparison of Major Explainable Artificial Intelligence Techniques

Technique	Explainability Type	Key Strength	Typical Applications	Reference
SHAP	Global & Local	Consistent feature attribution	Healthcare, Finance, Risk Prediction	Ali et al. (2023)
LIME	Local	Instance-level interpretation	Classification and Decision Support	Angelov et al. (2021)
Attention-Based	Model-Specific	Highlights influential input features	NLP, Healthcare, Vision	Amjad et al. (2023)
Counterfactual Explanations	Local	Actionable decision insights	Decision Support, Recommendation Systems	Chamola et al. (2023)
Causal Explainability	Global	Identifies cause–effect relationships	Scientific Analysis, Policy Decisions	Devireddy (2025)

5. HYBRID EXPLAINABLE AI–DEEP LEARNING FRAMEWORKS

The combination of high predictive performance with transparent and interpretable decision-making has led to the development of intelligent decision support systems, which has encouraged hybrid Explainable Artificial Intelligence (XAI)–deep learning frameworks as a promising approach. Unlike traditional deep learning models, which are black boxes, hybrid models add explainability mechanisms across the learning process, making it possible to gain insight into the reasoning behind the model's predictions. Generally, they combine deep neural networks with explanation modules, knowledge-based systems, semantic reasoning, or feature attribution methods, to enhance the reliability of the decisions while preserving analytical accuracy. This all-in-one solution aids in informed decision-making in various domains such as healthcare, cybersecurity, finance, manufacturing, and more (Chernenkiy et al., 2018; Zou & Miao, 2025).

Hybrid frameworks are effective when their integration approach is carefully considered in developing the model. Explainability can be introduced into the architectures in an intrinsic or post hoc manner or a combination thereof that makes use of the intrinsic and post hoc. While model-agnostic methods can leverage the predictions of different learning algorithms, model-specific methods can capitalize on the built-in structure of deep learning models to yield more detailed explanations. Moreover, attention mechanisms have gained significance in the field of computer vision for determining influential features and in making the architectures of transformer networks and neural networks transparent, especially in large-scale applications like natural language processing (NLP) and healthcare. (Devireddy, 2025; Amjad et al., 2023).

In addition to technical capabilities, hybrid XAI frameworks highlight the importance of human-centred decision intelligence, making sure that the recommendations produced by AI are comprehensible, credible and implementable for end users. By incorporating user experience (UX) principles into AI design, the collaboration between humans and Intelligent Systems is deepened, along with the acceptance, accountability, and confidence in the decision made. Therefore, transparency, fairness, robustness and ethical responsibility are key principles in the decision-making process for trustworthy frameworks. These enhancements are further compounded by the development of multi-model hybrid architectures and explainable foundation models, which integrate a variety of learning paradigms with scalable mechanisms for explainability, allowing for intelligent decision support systems to tackle the more complex challenges of the real world, while ensuring both trust and regulatory compliance with the user (Boger, 2019; Szilagyi & Wira, 2018). Figure 2 shows the architecture of a hybrid Explainable AI (XAI)–deep learning system, which transforms heterogeneous data sources into data, deep learning models, explainability techniques, and human-centered decision support, ensuring intelligent decision-making in smart digital ecosystems is transparent and trustworthy.

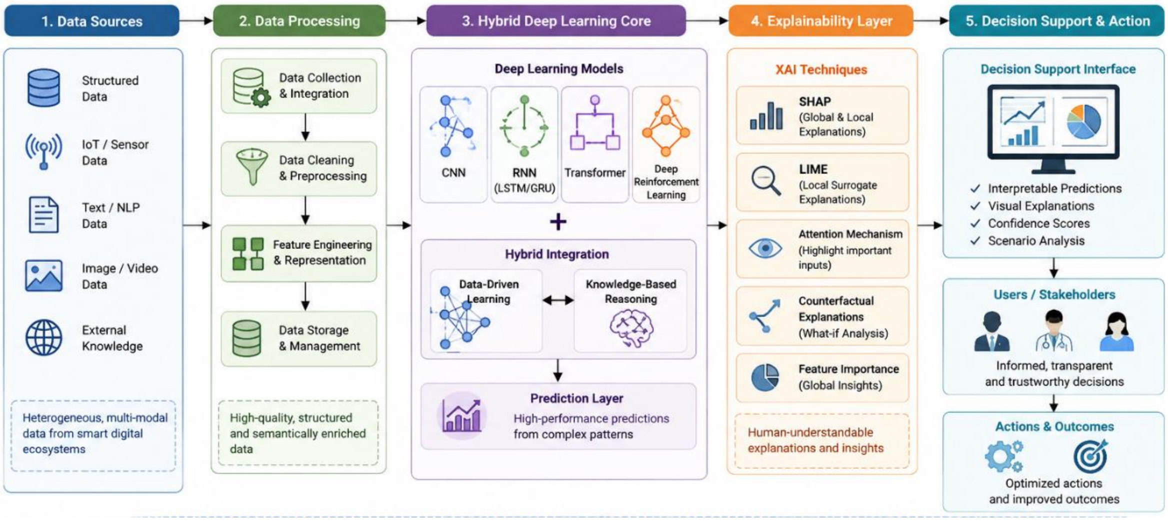

Figure 2. Hybrid Deep Learning and Explainable AI Architecture for Trustworthy Decision Intelligence

6. APPLICATIONS ACROSS SMART DIGITAL ECOSYSTEMS

Explainable Artificial Intelligence (XAI) and deep learning models have greatly enhanced the functionality of Intelligent Decision Support Systems (IDSS) in the context of smart digital ecosystems. In the medical field, these systems aid in diagnosis, clinical decision-making, patient tracking, and tailored treatment, while providing clear explanations and reliable predictions, which enhances the trust between clinicians and patients and boosts patient safety. The introduction of sensor-enabled digital twins further bolsters the real-time health monitoring and predictive healthcare management (Adibi et al., 2024).

Hybrid AI models are particularly useful in smart manufacturing for predictive maintenance, quality control, process automation, and resource management, as they continuously monitor systems and processes, providing intelligent analysis and insights. Likewise, in finance, explainable deep learning is used to detect fraud, manage credit risk, analyze investment opportunities, and ensure regulatory compliance, allowing financial institutions to maintain a delicate balance between accuracy and transparency. In smart cities, intelligent decision support system helps to optimize traffic, energy usage, and monitor the environment and urban life, while in digital twin technologies, city infrastructure optimization and real-time simulation are used to manage sustainable city development (Mylonas et al., 2021).

In the transportation and autonomous systems sectors, hybrid AI is transforming the field of decision support with explainable AI, optimizing routes, self-driving car navigation, traffic safety, and mobility management. Transparent AI recommendations enhance the trust of the user and enable safer human-robot interactions (Hancock et al., 2019). Aside from transport, intelligent decision support also plays a role in cyber security (anomaly detection and threat intelligence), agriculture (precision farming and monitoring crops), education (personalized assessment and adaptive learning), the supply chain and logistics (forecasting and optimizing operations), and the Industrial Internet of Things (IIoT) (predictive maintenance, intelligent automation, and real-time operational control). All these multidisciplinary applications highlight the fact that hybrid Explainable AI–deep learning applications are essential to trusted, adaptive, and human-centric smart digital ecosystems to enable sustainable digital transformation (Hurrah et al., 2023; Boger, 2019). Table 3 provides an overview of the key application domains of the hybrid Explainable AI (XAI) / deep learning systems and their application-specific values for smart digital ecosystem intelligent decision support.

Table 3. Applications of Hybrid Explainable AI–Deep Learning in Smart Digital Ecosystems

Domain	Major Applications	Key Benefit	Reference
Healthcare	Diagnosis, patient monitoring, digital twins	Accurate and interpretable clinical decisions	Adibi et al. (2024)
Smart Manufacturin g	Predictive maintenance, quality control	Improved productivity and automation	Mylonas et al. (2021)
Smart Cities	Traffic, energy, infrastructure management	Sustainable urban decision-making	Mylonas et al. (2021)
Transportation	Autonomous driving, traffic optimization	Safe and transparent mobility	Hancock et al. (2019)
IIoT & Smart Ecosystems	Predictive analytics, intelligent automation	Adaptive and sustainable operations	Hurrah et al. (2023)

8. CHALLENGES, RESEARCH GAPS, AND FUTURE DIRECTIONS

While hybrid Explainable Artificial Intelligence (XAI) and deep learning frameworks have been a significant step forward in intelligent decision support, there are still several challenges that prevent their widespread use. One significant challenge is the trade-off between predictive accuracy and explainability, especially when a model is very complex, it may not be explainable. The scalability and computational complexity also limit the use of these frameworks to real-time, data-intensive smart digital ecosystems, especially in resource-constrained settings. There are also privacy, cybersecurity, fairness, and ethical governance of AI concerns that are uninvestigated, particularly in case of the processing of sensitive data from interconnected platforms. Furthermore, biased datasets and opaque learning algorithms can also compromise confidence and result in unfair or inaccurate outcomes. One major research challenge is the lack of standardized metrics for explainability, which makes it difficult to objectively assess and compare explainability techniques for various application areas. However, effective human-AI collaboration also demands intuitive explanations that boost user trust without adding to their cognitive load. Moving forward, it is crucial to focus on scalable, efficient, privacy-aware, and human-centric hybrid approaches incorporating explainability at every stage in the decision-making process. Provements in explainability, federated intelligence, trustworthy foundation models, common evaluation metrics and ethical AI governance will further bolster transparency, accountability and robustness, and help meet the growing demands of next-generation smart digital ecosystems.

9. CONCLUSION

With the emergence of the new paradigm of AI for intelligent decision support systems that are not only accurate but also explainable, reliable and human-oriented, the technology of Hybrid Explainable Artificial Intelligence (XAI) and deep learning have been recognized as complementary approaches. In this review, the development of intelligent decision support in smart digital ecosystems has been highlighted, with a focus on the impact of the improvement of deep learning architectures, explainability techniques and hybrid approaches on the data-driven decision making in various application areas, such as healthcare, manufacturing, finance, transportation, smart cities and others. The synthesis also showed that explainability can be used to improve the interpretability of deep learning models, which can increase user trust, regulatory compliance, and collaboration in human-AI decision-making while maintaining the models' analytical power. Meanwhile, issues of scalability, computation, privacy, bias, ethics of governance, and not having a standardized method of measuring explainability are still major issues. Such future explainable decision support systems are predicted to be further enhanced by emerging technologies such as federated learning, digital twins, multimodal AI, and intelligent IoT (internet of things) ecosystems. Next steps for research should focus on creating scalable, privacy preserving and ethically sound hybrid models that effectively incorporate predictive intelligence and explanations. These will help advance the trustworthy use of AI and pave the way for intelligent decision support systems to be an integral part of smart digital ecosystems across various industrial and societal applications that are resilient, adaptive and sustainable.

REFERENCES

1. Adibi, S., Rajabifard, A., Shojaei, D., & Wickramasinghe, N. (2024). Enhancing healthcare through sensor-enabled digital twins in smart environments: A comprehensive analysis. Sensors, 24(9), 2793.
2. Ali, S., Abuhmed, T., El-Sappagh, S., Muhammad, K., Alonso-Moral, J. M., Confalonieri, R., ... & Herrera, F. (2023). Explainable Artificial Intelligence (XAI): What we know and what is left to attain Trustworthy Artificial Intelligence. Information fusion, 99, 101805.
3. Amjad, H., Ashraf, M., Sherazi, S., Khan, S., Fraz, M. M., Hameed, T., & Bukhari, S. A. C. (2023). Attention-based explainability approaches in healthcare natural language processing.
4. Angelov, P. P., Soares, E. A., Jiang, R., Arnold, N. I., & Atkinson, P. M. (2021). Explainable artificial intelligence: an analytical review. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 11(5), e1424.
5. Beshley, M., Klymash, M., Beshley, H., Shkoropad, Y., & Bobalo, Y. (2024, February). Revolutionizing Digital Ecosystems with Artificial Intelligence: Challenges, Concepts, and Future Directions. In IEEE International Conference on Advanced Trends in Radioelectronics, Telecommunications and Computer Engineering (pp. 1-21). Cham: Springer Nature Switzerland.
6. Boger, J. (2019). Human centered artificial intelligence: weaving UX into algorithmic decision making.
7. Chamola, V., Hassija, V., Sulthana, A. R., Ghosh, D., Dhingra, D., & Sikdar, B. (2023). A review of trustworthy and explainable artificial intelligence (XAI). IEEe Access, 11, 78994-79015.
8. Chen, Z., Xu, L., Zheng, H., Chen, L., Tolba, A., Zhao, L., ... & Feng, H. (2024). Evolution and Prospects of Foundation Models: From Large Language Models to Large Multimodal Models. Computers, Materials & Continua, 80(2).
9. Chernenkiy, V., Gapanyuk, Y., Terekhov, V., Revunkov, G., & Kaganov, Y. (2018). The hybrid intelligent information system approach as the basis for cognitive architecture. Procedia computer science, 145, 143-152.
10. Cichy, R. M., & Kaiser, D. (2019). Deep neural networks as scientific models. Trends in cognitive sciences, 23(4), 305-317.
11. Devireddy, K. (2025). A comparative study of explainable AI methods: Model-agnostic vs.

model-specific approaches. arXiv preprint arXiv:2504.04276.
12. Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. International journal of information management, 48, 63-71.
13. Fatima, M., Zia, R., & Usmani, I. A. (2025). A hybrid framework integrating deep learning and XAI for breast cancer detection with stratified cross-validation. Systems and Soft Computing, 200412.
14. Gadhave, R. T., Dhingra, S. K., Abhishek, M. B., Thota, M. K., Sholapurapu, P. K., Lamba, V., ... & Yadav, M. S. (2025). Deep Learning-Enabled Decision Support Systems For Strategic Business Management. International Journal of Environmental Sciences, 11(7), 2025.
15. Gillioz, A., Casas, J., Mugellini, E., & Abou Khaled, O. (2020, September). Overview of the Transformer-based Models for NLP Tasks. In 2020 15th Conference on computer science and information systems (FedCSIS) (pp. 179-183). IEEE.
16. Hancock, P. A., Nourbakhsh, I., & Stewart, J. (2019). On the future of transportation in an era of automated and autonomous vehicles. Proceedings of the National Academy of Sciences, 116(16), 7684-7691.
17. Hurrah, N. N., Khan, E., & Parah, S. A. (2023). Smart ecosystems for sustainable development: Opportunities, challenges, and solutions. Intelligent Multimedia Signal Processing for Smart Ecosystems, 3-28.
18. Jacobides, M. G., Brusoni, S., & Candelon, F. (2021). The evolutionary dynamics of the artificial intelligence ecosystem. Strategy Science, 6(4), 412-435.
19. Jain, P., Rathour, A., Sharma, A., & Chhabra, G. S. (2025). Bridging explainability and security: an xai-enhanced hybrid deep learning framework for iot device identification and attack detection. IEEE Access.
20. Maddukuri, N. (2023). Ai-Powered Decision Making In Rpa Workflows: The Rise Of Intelligent Decision Engines. Intelligence, 1(1), 72-86.
21. Mathew, D. E., Ebem, D. U., Ikegwu, A. C., Ukeoma, P. E., & Dibiaezue, N. F. (2025). Recent Emerging Techniques in Explainable Artificial Intelligence to Enhance the Interpretable and Understanding of AI Models for Human: DE Mathew et al. Neural processing letters, 57(1), 16.
22. Mijwil, M. M., Aggarwal, K., Sonia, S., Al-Mistarehi, A. H., Alomari, S., Gök, M., ... & Abdulrhman, S. H. (2022). Has the Future Started? The Current Growth of ArtificialIntelligence, Machine Learning, and Deep Learning. Iraqi Journal for Computer Science and Mathematics, 3(1), 13.
23. Mygal, V. P., Mygal, G. V., & Illiashenko, O. (2021). Intelligent decision support—cognitive aspects. In Digital Transformation, Cyber Security and Resilience of Modern Societies (pp. 395-411). Cham: Springer International Publishing.
24. Mylonas, G., Kalogeras, A., Kalogeras, G., Anagnostopoulos, C., Alexakos, C., & Muñoz, L. (2021). Digital twins from smart manufacturing to smart cities: A survey. Ieee Access, 9, 143222-143249.
25. Ocampo, A., Antonino, P. O., Capilla, R., & Nakagawa, E. Y. (2025). Digitalization of smart ecosystems. IEEE Software, 42(2), 33-37.
26. Renda, A., Ducange, P., Marcelloni, F., Sabella, D., Filippou, M. C., Nardini, G., ... & Baltar, L. G. (2022). Federated learning of explainable AI models in 6G systems: Towards secure and automated vehicle networking. Information, 13(8), 395.
27. Rodriguez-Garcia, P., Li, Y., Lopez-Lopez, D., & Juan, A. A. (2023). Strategic decision making in smart home ecosystems: A review on the use of artificial intelligence and Internet of things. Internet of Things, 22, 100772.
28. Sànchez-Marrè, M. (2022). Evolution of Decision Support Systems. In Intelligent Decision Support Systems (pp. 57-73). Cham: Springer International Publishing.
29. Sànchez-Marrè, M. (2022). Intelligent decision support systems. In Intelligent decision support systems (pp. 77-116). Cham: Springer International Publishing.
30. Secundo, G., Spilotro, C., Gast, J., & Corvello, V. (2025). The transformative power of artificial intelligence within innovation ecosystems: a review and a conceptual framework. Review of Managerial Science, 19(9), 2697-2728.
31. Sharifani, K., & Amini, M. (2023). Machine learning and deep learning: A review of methods and applications. World Information Technology and Engineering Journal, 10(07), 3897-3904.
32. Shuford, J. (2024). Deep reinforcement learning unleashing the power of AI in decision-making. Journal of Artificial Intelligence General Science, 1(1).
33. Szilagyi, I., & Wira, P. (2018, May). An intelligent system for smart buildings using machine learning and semantic technologies: A hybrid data-knowledge approach. In 2018 IEEE Industrial Cyber-Physical Systems (ICPS) (pp. 20-25). IEEE.
34. Taherdoost, H. (2023). Deep learning and neural networks: Decision-making implications. Symmetry, 15(9), 1723.
35. Van Hoang, T. (2024). Impact of integrated artificial intelligence and internet of things technologies on smart city transformation. Journal of technical education science, 19(Special Issue 01), 64-73.

36. Yu, Y., Si, X., Hu, C., & Zhang, J. (2019). A review of recurrent neural networks: LSTM cells and network architectures. Neural computation, 31(7), 1235-1270.

37. Zou, Y., & Miao, P. (2025). Explainable AI-enabled hybrid deep learning architecture for breast cancer detection. Frontiers in Immunology, 16, 1658741.