



Information Research – Vol. 31 No. iConf (2026)

Creating digital information with algorithms and artificial intelligence

Jessica K. Barfield

DOI: <https://doi.org/10.47989/ir31iConf64225>

Abstract

Introduction. This paper discusses the use of digital information for content creation, reviews different techniques of AI that are used to create digital information, and presents examples of algorithms that are used to create digital content. Further, the paper discusses how information created by AI is becoming essential in developing the emerging digital society.

Method. This paper is focused on concepts relating to the use of AI to create digital content and digital information. The method used is a review of current AI techniques used to create digital content including algorithms and other techniques of AI.

Analysis. As a concept paper, the focus is to provide a critical discussion of AI and algorithms with the goal to create digital information and content. The basics of creating digital information are presented as is a brief review of current machine learning algorithms.

Results. The discussion presented in the paper highlights the increasing use of algorithms in society and that issues associated with information science and ethics are impacted by the use of AI.

Conclusions. The paper concludes with a discussion of future directions in the use of AI-generated information for smarter and more agentic computing systems.

Introduction

This paper discusses how information and digital content are created using algorithms and other techniques of artificial intelligence (AI) and how information created by AI is becoming essential in developing the emerging digital society. Considering techniques used by AI, the concept of AI information has two primary meanings. The first refers to the information contained in the datasets used to train AI systems allowing AI to learn, reason, and perform tasks such as identifying patterns and making predictions (Rather et al. 2024). Information from datasets is also essential for AI to function and to understand human language, recognise objects, and automate complex processes. The second meaning associated with AI information refers to the actual use of AI-generated information which, among others, is helping to create the emerging digital society and in influencing developments in education, healthcare, and commerce (Popkova and Gulzat, 2020). This paper first reviews how AI creates information, then discusses different types of AI techniques including algorithms which are used to create digital content, and concludes with a discussion of future directions in the use of AI towards the creation of a digital society.

As a broad overview of AI, three types of AI are often discussed. First, weak (or narrow) AI, which is the current form of AI, is designed to perform specific tasks by operating with human-like abilities (Bory, Natale, and Katzenbach, 2025). For example, with weak AI, a program may be designed to play chess by applying algorithms which direct the movement of chess pieces during a game. However, in terms of the tasks it can perform, weak AI cannot perform beyond its programmed abilities. Secondly, there is an ongoing effort to create strong (or general) AI which is a more general form of AI which theoretically will be able to operate with human-like intelligence, understanding, and reasoning abilities (Butz, 2021). While strong AI is not currently available, applications that are discussed include completely autonomous vehicles that would be capable of handling complex and unpredictable highway scenarios, and highly personalised AI-driven tutors (Baillifard, Gabella, and Lavenex, (2025). Thirdly, while admittedly an even more future-oriented possibility, superintelligent AI may eventually be created and if so, will represent an advanced form of AI that surpasses human intelligence in all aspects (Bostrom, 1998). This type of AI could potentially outperform humans in every field, from scientific research to social skills. Considering the human understanding of AI's problem-solving abilities, strong AI and superintelligence raises the 'black-box issue' (Figure 1) (Hassija et al. 2024). That is, an AI system whose internal workings are beyond an individual's ability to understand the functioning of the AI system, thus raising numerous societal issues such as determining liability should the AI system harm individuals and ethical issues based on the AI's problem-solving abilities. Essentially, with strong AI users could see the system's inputs and experience the AI systems outputs, but not understand what happens within the AI system that produces those outputs.

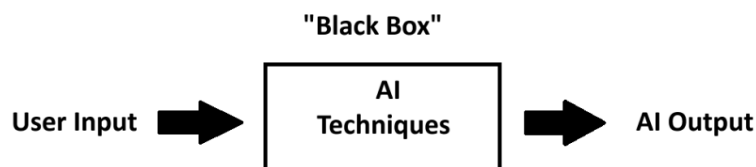


Figure 1. AI techniques, if not understood, are thought to create a 'black-box' which can be viewed in terms of its inputs and outputs (or transfer characteristics), without an understanding of its internal workings.

Considering more specifically the concept of digital information, information that is created by AI techniques represent data that has been processed, organised, and structured to have meaning and context thus making it useful for humans and systems (Agerfalk, 2020). With AI-based systems, digital information is expressed as bits and bytes through a process called binary encoding, where the data, whether it's text, images, or sounds, is converted into sequences of the binary digits 0 and 1 (Kaliappan et al. 2023). A bit of course is the smallest unit of digital information whereas a

byte consists of a group of eight bits and is a standard unit for data storage which allows for the representation of characters and more complex data. For example, a byte, consisting of 8 bits, could be represented by 10001011. Since each bit could be either 0 or 1, with 8 bits in a byte, there are 2^8 or 256 different values a byte could have. From this binary coding technique, to create information a byte, for example, could store a pixel with one out of 256 different colours or display a character from the ASCII table.

As an example of the use of AI leading to a digital society, within library science Jaillant and Caputo (2022) discussed the challenges faced by cultural heritage institutions. They commented that if AI was provided with enough sample data from which to learn and train their models, AI and more specifically machine learning algorithms, would offer the opportunity for AI to improve, and ease the access to digital archives. Additionally, as another example of AI leading to a digital society, in the medical domain Syed et al. (2023) discussed the use of AI to provide digital information that could be used to aid clinical decision-making by interpreting large datasets quickly. Each of these examples show the integration of digital information in society.

From the above brief discussion, as we approach an increasingly AI-integrated world, examining the implications of the design and use of digital information produced by AI systems will become crucial. Therefore, this paper explores the current and future direction of AI-generated information, discusses the evolving production of digital content, and discusses the potential transformations brought about by AI systems to society. By examining these aspects of AI, we can gain valuable insights into the challenges and opportunities that lie ahead in the realm of content creation and digital information consumption with the goal to manage them more successfully (Floridi, 2024). The research objective guiding this paper is to identify gaps in the literature on the use of AI to create a digital society.

Digital content

Discussing content produced by AI, the production of digital content should consist of well-formed and meaningful data (Landgrebe and Smith, 2021). And considering that creating digital information is dependent on data, the structure of digital data—their syntax—determines their ‘well-formedness’ while their meaning constitutes their semantics (Floridi, 2024). For structured data, digital content examples include blogs, news, social media posts, pictures, podcasts, video clips, or interactive computer games. Further, to produce content, AI often uses machine learning algorithms trained on large datasets to produce audio, textual, video, and visual content and done with quality, speed, and scale in ways that are becoming increasingly available (*involving more potential producers*), *accessible* (*lower skills required*), *affordable* (*less expensive or capital-intensive*), and *potentially interactive*’ (Florida, 2024, pg.112).

As AI technology continues to advance, the creation of digital information will challenge our traditional understanding of content and, among others, open up new possibilities for the creation and consumption of digital information (Wang et al. 2023). However, from the use of digital information there are risks to an evolving digital society. For example, AI produced content raises crucial and challenging questions about the authenticity, attribution, reliability, accountability, responsibility, and transparency of digital information. Thus, as information becomes more integrated into society, distinguishing between human and AI-produced content will become increasingly difficult, raising trade-offs that will require new ethical frameworks as well as new policies and strategies (Elkhatat, et al. 2023). As a summary of the discussion to this point, Figure 2 shows three major techniques of AI used to generate digital information and with implications for the evolving digital society.

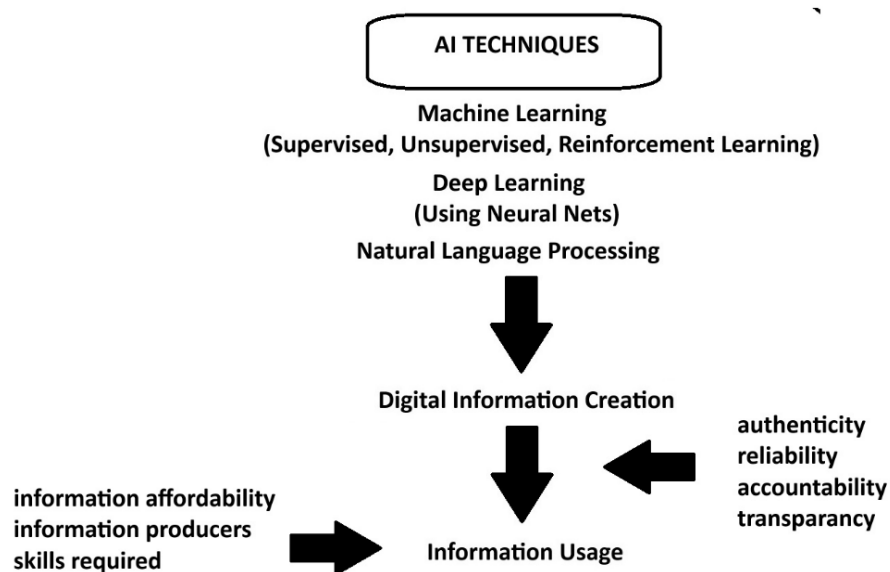


Figure 2. AI techniques used to create digital content and influence information usage.

In a discussion of digital content created by AI techniques traditional communication and information models have been successfully used in guiding our understanding of the evolving digital information infrastructure (Levin and Mamlok, 2021). There are several techniques used by AI techniques to create digital content. For example, data is necessary to produce content when AI models are trained on large datasets which contain text, images, and code. In addition, through deep learning techniques AI is able to learn the underlying patterns, structures, and relationships within data (LeCun, Bengio, and Hinton, 2015). With deep learning, if the goal is content generation, then when given a user prompt, machine learning algorithms use learned patterns to generate new content that mimics the style and characteristics of its training data (Liu et al. 2021). With prompting, the quality of the output (that is, information created) is highly dependent on the quality of the input prompt, which is the instruction or question provided by the user (Ronanki et al, 2024). For example, GenAI is a type of AI that can create new and original content, such as text, images, or music, by learning from vast amounts of existing data. Among others, GenAI is challenging our understanding of content and traditional notions of authorship and transforming the relationship between content producers and consumers (Felix, 2025). Effective use of machine learning requires a critical evaluation of the AI's output for accuracy, originality, and potential biases (Lebovitz et al. 2021).

Considering GenAI as part of an information system whose purpose is to create content, from the perspective of machine learning, as noted above, the input to the AI system is the user's prompt, and the output is the model's response – the generated content. Given AI's sophistication and how it functions, machine learning techniques used to produce content can be understood as a transmission channel operating in a computable manner (Straňák, 2025). The transmission channel, starting from the user's input, to the AI's output, is represented by information from training data encoded in the model's machine learning weights that is, in the transformer technology or neural net architecture used in the machine learning model. Given the input-output nature of producing digital content with AI, Shannon's information model applies to the functioning of the machine learning model which among other discusses the concept of data compression in an information channel. Machine learning and data compression are closely related fields with the core idea linking them the ability of a system to model and predict data, which is fundamental to the development of a digital society (Larrakoetxea et al. 2023).

Considering Shannon's (1998) information model, it has a number of implications for machine learning models that are used to create digital content. Shannon's information processing model states that no data processing can increase the amount of information that data carries about the original source (Lombardi, Holilk, and Vanni, 2016). Data processing can only preserve information (in the ideal case of lossless encoding) or reduce it (in the case of lossy processing or in the presence of noise) (Jain et al. 2018). Note that lossless encoding is a data compression method where information is reduced by identifying and eliminating statistical redundancy, allowing for the perfect reconstruction of the original data after decompression (Reagan et al. 2018). In addition, the quantisation of weights and activations in a neural network is a form of lossy processing (Chen et al. 2024). For example, quantising weights from 32-bit to 8-bit reduces the precision of representation, leading to approximation and thus a loss of detail in the data. In lossy data compression, the reconstruction signal need not be identical to the source signal, but should satisfy a certain fidelity constraint (Chen et al. 2024).

Types of AI and algorithms used to create information

There are different ways to categorise techniques of AI which relates to their ability to create digital information and digital content. For example, an introduced above, an important AI technique, machine learning, enables systems to learn and improve from experience without being explicitly programmed by users (El Naqa and Murphy, 2015). Machine learning relies on algorithms and statistical models to create information and to analyse and draw inferences from data. A key type of machine learning model is supervised learning which involves training a model based on labelled data, where the desired output is known (El Mrabet et al. 2021). Examples of supervised learning techniques which can be used to create digital content include linear regression, classification algorithms, and support vector machines (a technique which separates datapoints into different classes) (Suthaharan, 2016). Essentially supervised learning algorithms learn from labelled data, meaning the input data is paired with the correct output. The goal of the algorithm is to learn a mapping function from input to output so that the algorithm can predict the output for new, unseen inputs (Baldi et al. 2000). In addition, supervised learning is used in image recognition, fraud detection, and for other applications supporting the emerging digital society. In contrast, unsupervised learning involves training a model on unlabelled data, where the output is not predefined by a user and algorithmic techniques include clustering and association (Dike et al. 2018; James et al. 2023). Additionally, deep learning creates digital information using different types of algorithms and uses artificial neural networks with many layers (deep networks) (Schmidhuber, 2015). Examples of algorithms for deep learning include clustering algorithms such as K-means clustering, and hierarchical clustering, which are used to group similar data points together (Shrestha, 2019).

Another type of AI algorithm used to create digital information is reinforcement learning which involves an AI agent learning to make decisions to maximise a reward signal (Arulkumaran et al. 2017). The agent learns through trial and error, taking actions and receives feedback in the form of rewards or penalties. Examples of algorithms in this area include Q-learning, the state-action-reward-state-action algorithm, and deep Q-networks which are used in applications such as gaming and the development of autonomous systems (Qiang and Zhongli, 2011). Beyond the above algorithm categories, semi-supervised learning is another type of algorithmic approach that combines elements of both supervised and unsupervised learning, utilising a small amount of labelled data alongside a larger amount of unlabelled data for model training (van Englen and Hoos, 2020).

Next, I provide a discussion of different features of algorithms that are used to create digital information. To begin, the sorting of information is often a major aspect of a task when creating digital content (Beus, 1970). Sorting is the process of arranging elements in a data structure such as an array, into a specific order (e.g., ascending or descending) (Yu and Xiao, 2022). Algorithms

that perform this task are categorised mainly as comparison-based (e.g., bubble sort, quick sort, and merge sort) and non-comparison-based (e.g., counting sort, radix sort, and bucket sort) algorithms (Hammad, 2015). Further, comparison-based sorting algorithms are used to determine the order of elements by comparing them to one another. An example includes a bubble sort which compares adjacent elements and swaps them if they are in the wrong order (Min, 2010). Further, a selection sort is an algorithm that repeatedly finds the minimum element from the unsorted part and places it at the beginning (Edjlal et al. 2011). In addition, a merge sort is a divide-and-conquer algorithm that divides a list of items, sorts the sub-lists, and then merges them (Lobo and Kuwelkar, 2020; Ala'Anzy et al. 2024; de Gouw et al. 2016). While the above is a brief summary it highlights some of the techniques used to produce digital information and content.

Conclusions and future directions

The emergence of increasingly powerful and sophisticated AI techniques producing digital information represents an emerging direction in content production, dissemination, and consumption of digital information (Cao et al. 2023). As society confronts these new scenarios, it is crucial to consider both the opportunities and challenges presented by AI created content. For example, AI generated content may give rise to new forms of cultural exchange within the digital society. Beyond current forms of generative AI agentic AI will consist of multiple specialised AI agents that work together to accomplish complex multi-step workflows with greater autonomy (Acharya, Kuppan, and Divya, 2025). It is also expected that future AI will be able to process and integrate information from multiple sources simultaneously, including text, voice, visuals, and even facial expressions. Further, innovations like neuromorphic computing which mimics the human brain, and optical computing, which uses light instead of electricity, will likely boost processing efficiency (Apostolos, 2022; Rietsche et al. 2022). In this area, another trend is that with human-generated data potentially running out, AI is shifting towards synthetic data, or artificial datasets that mimic real-world patterns. Finally, as a key driver for future AI development, research is focused on moving models beyond basic pattern recognition toward advanced reasoning, decision-making, and problem-solving. Even further in the future, self-aware AI may be developed which would be a form of AI with consciousness.

Acknowledgement

The author acknowledges the School of Information Science at the University of Kentucky-Lexington for support during the writing of this manuscript.

About the author

Jessica Barfield is an Assistant Professor in the school of Information Science at the University of Kentucky-Lexington. Her research involves usability studies on AI, robotics, and ethical issues in the design and use of smart technology. She can be contacted at jessicabarfield@uky.edu

References

- Acharya, D.B., Kuppan, K., and Divya, B., 'Agentic AI: Autonomous Intelligence for Complex Goals—A Comprehensive Survey,' IEEE Access, Vol. 13, 18912-18936, 2025
- Ala'Anzy, M. A., Mazhit, Z., Ala'Anzy, A. F., Algarni, A., Akhmedov, R., and Bauyrzhan, A., 'Comparative Analysis of Sorting Algorithms: A Review,' 11th International Conference on Soft Computing & Machine Intelligence (ISCM), 88-100, 2024.

- Apostolos, A., Photonic Neuromorphic Technologies in Optical Communications, *Nanophotonics*, Vol. 11(5), 897-916, 2022.
- Arulkumaran, K., Deisenroth, M. P., Brundage, M., and Bharath, A. A., Deep Reinforcement Learning: A Brief Survey, *IEEE Signal Processing Magazine*, Vol. 34(6), 26-38, 2017.
- Baldi, P., Brunak, S., Chauvin, Y., Andersen, C. A. F., and Nielsen, H., Assessing the Accuracy of Prediction Algorithms for Classification: An Overview, *Bioinformatics*, Vol. 16(5), 412-424, 2000.
- Baillifard, A., Gabella, M., Lavenex, P.B. et al. Effective Learning With a Personal AI Tutor: A Case Study, *Educ Inf Technol*. Vol. 30, 297-312, 2025.
- Beus, H. L., The Use of Information in Sorting, *Journal of the ACM (JACM)*, Vol. 17(3), 482 – 495, 1970.
- Bory, P., Natale, S. and Katzenbach, C., Strong and Weak AI Narratives: An Analytical Framework, *AI & Soc.*, Vol. 40, 2107-2117, 2025.
- Bostrom, N., How Long Before Superintelligence? *Int. Jour. of Future Studies*, Vol. 2, 1998.
- Butz, M. V., Towards Strong AI, *Künstl Intell.*, Vol. 35, 91-101, 2021.
- Cao, Y., Li, S., Liu, Y., Yan, Z., Dai, Y., Yu, P.S., and Sun. L.,, A Comprehensive Survey of AI-Generated Content (AIGC): A History of Generative AI from GAN to ChatGPT, *arXiv:2303.04226*, 2023.
- Chen, J., Fang, Y., Khisti, A., Özgür, A., Shlezinger, N., and Tian, C., Information Compression in the AI Era: Recent Advances and Future Challenges, *arXiv:2406.10036v1 [cs.IT]*, 2024.
- de Gouw, S., de Boer, F. S., and Rot, J., Verification of Counting Sort and Radix Sort. In: Ahrendt, W., Beckert, B., Bubel, R., Hähnle, R., Schmitt, P., Ulbrich, M. (eds) *Deductive Software Verification – The KeY Book. Lecture Notes in Computer Science*, Vol. 10001, Springer, Cham., 2016.
- Dike, H. U., Zhou, Y., Deveerasetty, K. K., and Wu, Q., Unsupervised Learning Based On Artificial Neural Network: A Review, *IEEE International Conference on Cyborg and Bionic Systems (CBS)*, 322-327, 2018.
- Edjlal, R., Edjlal, A., and Moradi, T., A Sort Implementation Comparing with Bubble Sort and Selection Sort, *3rd International Conference on Computer Research and Development*, 380-381, 2011.
- Elkhatat, A.M., Elsaid, K. and Almeer, S., Evaluating the Efficacy of AI Content Detection Tools in Differentiating Between Human and AI-Generated Text, *Int J Educ Integr.*, Vol. 19, 17, 2023.
- El Naqa, I., and Murphy, M. J., What Is Machine Learning? In: El Naqa, I., Li, R., Murphy, M. (eds) *Machine Learning in Radiation Oncology*, Springer, Cham., 2015.
- El Mrabet, M.A., El Makkaoui, K., and Faize, A., Supervised Machine Learning: A Survey, *4th International Conference on Advanced Communication Technologies and Networking (CommNet)*, 1-10, 2021.
- Felix, J. F., And the Author Is ... ChatGPT, *Respiration*, Vol. 10(4), 229-230, 2025.
- Floridi, L., On the Future of Content in the Age of Artificial Intelligence: Some Implications and Directions, *Philos. Technol.*, Vol. 37, 112, 2024.

- Hammad, J., A Comparative Study Between Various Sorting Algorithms, *IJCSNS International Journal of Computer Science and Network Security*, Vol.15(3), 2015.
- Hassija, V., Chamola, V., Mahapatra, A. et al. Interpreting Black-Box Models: A Review on Explainable Artificial Intelligence, *Cogn Comput.*, Vol. 16, 45–74, 2024.
- Jaillant, L., and Caputo, A. Unlocking Digital Archives: Cross-Disciplinary Perspectives on AI and Born-Digital Data, *AI & Soc.*, Vol. 37, 823–835, 2022.
- Jain, A., Phanishayee, A., Mars, J., Tang, L., and Pekhimenko, G., Gist: Efficient Data Encoding for Deep Neural Network Training, *ACM/IEEE 45th Annual International Symposium on Computer Architecture (ISCA)*, 776–789, 2018.
- James, G., Witten, D., Hastie, T., Tibshirani, R., and Taylor, J., *Unsupervised Learning*, In: *An Introduction to Statistical Learning*, Springer Texts in Statistics, Springer, Cham, 2023.
- Kaliappan, S., Maranan, R., Ali, H. M., and Yamsani, N., A Comprehensive Study on the Integration and Impact of Bits and Bytes in the Digital Era, *IEEE International Conference on ICT in Business Industry & Government (ICTBIG)*, 1–6, 2023.
- Landgrebe, J., and Smith, B. Making AI Meaningful Again, *Synthese*, Vol. 198, 2061–2081, 2021.
- Larrakoetxea, N. G., Astobiza, J. E., López, I. P., Urquijo, B. S., Barruetabeña, J. G., and Rego, A.Z., Efficient Machine Learning on Edge Computing Through Data Compression Techniques, *IEEE Access*, Vol. 11, 31676–31685, 2023.
- Lebovitz, S., Levina, N., and Lifshitz-Assaf, H., AI Ground Truth Really True? The Dangers of Training and Evaluating AI Tools Based on Experts' Know-What, *MIS Quarterly*, Vol. 45(3), 1501–1526, 2021.
- LeCun, Y., Bengio, Y. and Hinton, G., Deep Learning, *Nature*, Vol. 521, 436–444, 2015.
- Levin, I., and Mamlok, D. Culture and Society in the Digital Age, *Information*, Vol. 21, 12(2), 68, 2021.
- Liu, J., Snodgrass, S., Khalifa, A. et al. Deep Learning for Procedural Content Generation, *Neural Comput & Applic.*, Vol. 33, 19–37, 2021.
- Lobo, J., and Kuwelkar, S., Performance Analysis of Merge Sort Algorithms, *International Conference on Electronics and Sustainable Communication Systems (ICESC)*, 110–115, 2020.
- Lombardi, O., Holik, F. and Vanni, L. What is Shannon Information?. *Synthese*. Vol. 193, 1983–2012, 2016.
- Min, W., Analysis on Bubble Sort Algorithm Optimisation, *International Forum on Information Technology and Applications*, 208–211, 2010.
- Popkova, E. G., and Gulzat, K., Technological Revolution in the 21st Century: Digital Society vs. Artificial Intelligence. In: Popkova, E., Sergi, B. (eds) *The 21st Century from the Positions of Modern Science: Intellectual, Digital and Innovative Aspects*, ISC 2019, *Lecture Notes in Networks and Systems*, Vol. 91, Springer, Cham, 2020.
- Qiang, W., and Zhongli, Z., Reinforcement Learning Model, Algorithms and its Application, *International Conference on Mechatronic Science, Electric Engineering and Computer (MEC)*, 1143–1146, 2011.
- Rather, I. H., Kumar, S. and Gandomi, A. H., Breaking the Data Barrier: A Review of Deep Learning Techniques for Democratising AI with Small Datasets, *Artif Intell Rev.*, Vol. 57, 226, 2024.

- Reagan, B., Gupta, U., Adolf, B., Mitzenmacher, M., Rush, A., Wei, G. and Brooks, D., Weightless: Lossy Weight Encoding for Deep Neural Network Compression. Proceedings of the 35th International Conference on Machine Learning, 2018, Available from <https://proceedings.mlr.press/v80/reagan18a.html>.
- Rietsche, R., Dremel, C., Bosch, S. et al. Quantum Computing, Electron Markets. Vol. 32, 2525–2536, 2022.
- Ronanki, K., Cabrero-Daniel, B., Horkoff, J., and Berger, C., Requirements Engineering Using Generative AI: Prompts and Prompting Patterns. In: Nguyen-Duc, A., Abrahamsson, P., Khomh, F. (eds) Generative AI for Effective Software Development, Springer, Cham., 2024.
- Schmidhuber, J., Deep Learning in Neural Networks: An Overview, Neural Networks, Vol. 61, 85–117, 2015.
- Shannon, C. E. and Weaver, W., The Mathematical Theory of Communication (University of Illinois Press: Urbana), 1998.
- Shrestha, A., and Mahmood, A., Review of Deep Learning Algorithms and Architectures, in IEEE Access, Vol. 7, 53040–53065, 2019.
- Straňák, P., Shannon's Theory of Communication - A Key to Understanding AI Model Collapse? 1–8, Available at: [file:///C:/Users/Woody/Downloads/Shannon's%20Theory%20of%20Communication%20-%20A%20Key%20to%20Understanding%20AI%20Model%20Collapse%20\(4\).pdf](file:///C:/Users/Woody/Downloads/Shannon's%20Theory%20of%20Communication%20-%20A%20Key%20to%20Understanding%20AI%20Model%20Collapse%20(4).pdf).
- Suthaharan, S., Support Vector Machine, In: Machine Learning Models and Algorithms for Big Data Classification. Integrated Series in Information Systems, Vol 36, Springer, Boston, MA, 2016
- Syed, S. M., Gopi, B., Mariam, K., Raheel, A., Siddiqui, M. K., and Agha, D., How Does Artificial Intelligence Impact Digital Healthcare Initiatives? A Review of AI Applications in Dental Healthcare, International Journal of Information Management Data Insights, Vol. 3(1), 2023.
- van Engelen, J. E., Hoos, H. H., A Survey on Semi-Supervised Learning. Mach Learn, Vol. 109, 373–440, 2020.
- Wang, Y., Pan, Y., Yan, M., Su, Z., and Luan, T. H., A Survey on ChatGPT: AI-Generated Contents, Challenges, and Solutions, IEEE Open Journal of the Computer Society, Vol. 4, 280–302, 2023.
- Yu, Y., and Xiao, X., Generating Almost Descending Sequences to Reduce the Number of Movements in Sorting, IEEE Access, Vol. 10, 81094–81104, 2022.

© [CC-BY-NC 4.0](#) The Author(s). For more information, see our [Open Access Policy](#).