On Explainability in AI-Solutions:  
A Cross-Domain Survey

Simon D Duque Anton\textsuperscript{1}\textsuperscript{[0000\textminus{}0002\textminus{}4005\textminus{}9165]}, Daniel Schneider\textsuperscript{2}\textsuperscript{[0000\textminus{}0001\textminus{}5005\textminus{}3635]}, and Hans D Schotten\textsuperscript{2}\textsuperscript{[0000\textminus{}0001\textminus{}5005\textminus{}3635]}  

\textsuperscript{1} comlet Verteilte Systeme GmbH, 66482 Zweibruecken, Germany  
simon.duque-anton@comlet.de  
\textsuperscript{2} DFKI, 67663 Kaiserslautern, Germany  
{Daniel, Hans_Dieter}.{Schneider, Schotten}@dfki.de

\textbf{Abstract.} Artificial Intelligence (AI) increasingly shows its potential to outperform predicate logic algorithms and human control alike. In automatically deriving a system model, AI algorithms learn relations in data that are not detectable for humans. This great strength, however, also makes use of AI methods dubious. The more complex a model, the more difficult it is for a human to understand the reasoning for the decisions. As currently, fully automated AI algorithms are sparse, every algorithm has to provide a reasoning for human operators. For data engineers, metrics such as accuracy and sensitivity are sufficient. However, if models are interacting with non-experts, explanations have to be understandable.  

This work provides an extensive survey of literature on this topic, which, to a large part, consists of other surveys. The findings are mapped to ways of explaining decisions and reasons for explaining decisions. It shows that the heterogeneity of reasons and methods of and for explainability lead to individual explanatory frameworks.

\textbf{Keywords:} Artificial Intelligence \cdot Explainability \cdot Survey \cdot Cross-Domain.

\section{Introduction}

Industrial revolutions provided humanity with novel technologies that fundamentally changed fields of work, mostly in manufacturing and processing industries. Currently, the fourth industrial revolution is said to introduce flexibility and ad-hoc connectivity to once inflexible industrial Operational Technology (OT) networks. This newly integrated means of connectivity in industrial networks,
across physical factory boundaries, allows for new use cases and improved efficiency. Apart from the connectivity aspect, the introduction of Artificial Intelligence (AI) methods presents new paradigms. In industrial environments, AI methods are applied to production and resource planning [27], detection of anomalies in production processes [24,25,28], and improvement of processes [60]. Apart from industrial applications, AI methods lend themselves readily on other domains, such as finance and banking [11], medicine [32] and elderly care [51], autonomous driving [57,56], network management [58,39,40,22], and for control of unmanned vehicles [55,42], just to name a few. In all of these fields, automation and AI are intended to perform tedious and repetitive tasks to relieve workers. However, this autonomous performance of tasks requires trustworthy and understandable algorithms as an enabler. If a task is to be performed by an algorithm, the outcome must not deviate from expectations, jitters in the input data cannot change the outcome in an undesirable fashion. Especially regarding AI algorithms, understanding the reasoning behind a decision is complex and often hardly possible for human operators. This is an issue, especially regarding regulatory standards and acceptance issues of users. Consequently, AI algorithms need to be understandable and provide predictable outcomes in a reliable fashion to further their application. This need has created the term of Explainable Artificial Intelligence (XAI) that encompasses the need for AI methods to not only provide sound results, but also provide the reasoning in a useful and understandable manner.

This work aims at providing an overview of requirements as well as solutions for the explainability of AI algorithms. Works related to explainability in AI are discussed in Section 2. Methods and techniques for explaining outcomes of AI algorithms are introduced in Section 3. Common application scenarios that require explainable AI methods are presented in Section 4. This work is concluded in Section 5.

2 Related Work

This section captures an overview of related works discussing explainability of AI methods in different domains. A comprehensive overview is provided in Table 1. This table lists the respective work, the domain which is discussed and the method used to explain the decision or recommendation made by the AI method. Reddy discusses the requirements formulated by stakeholders for acceptance of AI decisions in medical treatment and research while formulating the point that some argue in favour of higher accuracy algorithms instead of well-explainable ones [52]. Neugebauer et al. present a surrogate AI model, that addresses parameter changes of the base model and consequently highlights the relevant parameters in the decision, aiding its explainability [48]. Vilone and Longo survey scientific research addressing XAI and categorise findings in human-based explanations that aim at mimicking human reasoning, and objective metrics such as accuracy [64]. Caro-Martínez et al. introduce a conceptual
model for e-commerce recommender systems that extends existing models with four ontological elements: User motivation and goals, required knowledge, the recommendation process itself, and the presentation to the user [15]. Liang et al. present a novel online Explainable Recommendation System (ERS) that, in contrast to commonly used offline ERSs, can be updated and instantly provides explanations with recommendations [44]. Holzinger and Müller discuss a mapping approach of explainability with causability [38]. That means creating links between the reasoning an AI algorithm implicitly makes and the intuitive conclusions humans draw. This is applied to the area of image-based pattern recognition in medical treatment. Ehsan et al. present a concept for integrating social transparency into XAI solutions [26]. They present a framework based on expert-interviews. Angelov et al. discuss the relation of AI algorithms with high accuracy and high explainability factors [6]. A taxonomy is provided, global vs. local model explanation techniques for different domains and algorithms are surveyed and set in context with the remaining challenges. Mohseni et al. provide a survey of existing literature that clusters available methods and research approaches respective to their design goals as well as evaluation measures [17]. Their framework is founded on the distinction between the provided categories. Belle and Papantonis evaluate feasible methods of explainability on the use case of a data scientist that aims to convince stakeholders [11]. Shin discusses the relation of causability and explainability in XAI and the influence on trust and user behaviour [59]. Singh et al. evaluate methods to explain AI conclusions in the medical domain [20]. Barredo Arrieta et al. present an extensive survey on literature and solutions in XAI on which they base requirements and challenges yet to conquer [9]. Ultimately, they create the concept of fair AI that explains and accounts for decisions made. Lundberg et al. introduce a game-theoretic model for optimal explanations in tree-based algorithms [46]. Local explanations are combined to obtain a global explanation of the trained tree in a human-understandable format. Ploug and Holm present the concept of contestable AI decision making in a clinical context [49]. Contestability means that the decision algorithm has to provide information to the data used, any system biases, system performance in terms of algorithmic metrics, and the decision responsibility carried by humans or algorithms. If the decision is contested, the algorithm has to provide insight that the alternate solution was considered as well and has been adequately taken into account. Arya et al. introduce a collection of explainability tools that are combined into a framework to provide researchers and data scientists with the opportunity to extract explanations for various algorithms [8]. Linardatos et al. introduce a survey and taxonomy, distinguishing between different types of interpretability in AI methods before presenting an exhaustive list of tools and methods [15]. Tjoa and Guan discuss challenges and risks of explainability in medical AI applications [62]. They survey existing solutions for different algorithm types while also introducing risks and challenges with existing solutions. Roscher et al. present an overview of methods to conserve scientific interpretability and explainability in natural sciences [53]. Beaudoin et al. introduce a framework for explainability that can be applied in
multidisciplinary settings [10]. Three steps are required to obtain the suitable method of explainability: First, define the contextual factors regarding the explanation. Second, analyse the tools available for the technical problem at hand and third, chose the suitable global and local explanation tools that are compared to seven factors of cost created by lacking explanation. Coeckelbergh discusses the ethical and philosophical responsibility of decisions made by AI algorithms and evaluates the responsibility of agents for their decisions in time and conditional dependencies [19]. Bhatt et al. introduce a framework based on findings of a study that investigates the target audience of explainability in AI [13]. They find that most explainability approaches are created for machine learning engineers to adapt their model. Consequently, they propose a framework that allows the choice of a target audience and adapts the explainability accordingly. Ammar and Shaban-Nejad present a recommendation system for mental health analysis that is based on ontological knowledge of the domain [5]. Zhang and Chen survey ERS and their uses for end-users as well as developers [60]. Confalonieri et al. discuss the historical implications of XAI and propose criteria for explanations deemed necessary for human understanding of explanations [20]. Amann et al. evaluate the legal, ethical and organisational aspects of AI decisions in the medical domain [4]. Chen et al. develop a dynamic ERS that monitors user preferences and maps them to aspects of a product review to increase recommendation quality [18]. Kuhn and Kacker apply the well-established problem of fault location in combinatorial testing, where a software fails only after input of several bogus values that have to be identified, to the explainability problem in AI [43]. Based on feature combinations, the importance of any given feature for the decision is derived and thus used to explain the decision making process. Kailkhura et al. present a methodology for explaining classifications of AI algorithms in the domain of chemical material sciences [41]. Well-known and established algorithms, such as XGBoost [17], are extended with explanations regarding analogies in decisions to mimic human reasoning as well as feature importance to provide insight into the model design. According to their methodology, an AI model used for scientific research has to be transparent, the output should be interpretable, and the scientific result has to be explainable. Several methods are surveyed with respect to their dimensions of interpretability and the required integration of domain knowledge into the models. Tonekaboni et al. discuss requirements and conditions for AI in medical studies [63]. Explainability in this context describes the justifiability of results to stakeholders and colleagues, meaning explanations need to take stakeholder interests into account. The three metrics identified in their work contain domain appropriate representation, meaning that different disciplines in the medical field require different sets of information. Second, potential accountability describes a workflow for follow-up checking of the model outcome, meaning in the further treatment, the model decision should be validated with additional lab tests or checking in on patients. Third, consistency means that results provided by AI models should only be based on clinical variables and that any change in variable, and consequently outcome, should encompass a different but fitting explanation. Wang et
Cashmore et al. discuss explainability as a service [16]. In an industrial planning scenario, the user is asked to provide alternative plans with constraints from which an automated planner derives constraints that are the basis for an automated plan. These constraints are used to justify the automatically generated plan. Hois et al. analyse the need for human-centric AI-based decision making and the subsequent context-dependant explanation [34]. Humans as users are the main focus of the explanation that has to be tailored to situation and context. Gade et al. introduce challenges and existing solutions for the application of explainability in various domains [28]. Samek et al. dedicate a book to an overview of challenges, solutions, and visualisation of XAI [54]. Gunning et al. summarise challenges and user expectations on XAI [30]. Holzinger et al. evaluate causability as the property of a model to provide reasoning in histopathological examples [37]. Ai et al. present a deep learning approach on knowledge bases for recommender systems to improve the explainability aspects of recommendations [3]. Bellini et al. introduce a knowledge-graph-based method to explain user recommendations, thus increasing user satisfaction and acceptance [12]. Hoffman et al. present metrics regarding the acceptance and satisfaction of users regarding the explainability in different XAI methods [33]. Hagras discusses the challenges in XAI with a focus on dimensions of explainability as well as mapping of output to interpretation [31]. They discuss the necessity of rule-based mapping of decisions to explanations as well as labels and introduce fuzzy logic systems that can be used to explain class affiliation in a human-understandable fashion. Adadi and Berrada introduce a survey of concepts and challenges in XAI [2]. Abdollahi and Nasraoui evaluate the fairness of ERSs in the context of health, justice, education, and criminal investigations [1]. Holzinger provides a positional paper discussing the need for context-adaptive procedures in AI in order to make decisions understandable for humans [35]. Goebel et al. discuss the need for XAI in the context of increasingly complex AI systems [29]. Interactions between data points that can be represented in a graph can function as vectors of explainability, as these areas with high importance can be identified. Preece provides a survey and taxonomy of challenges and a possible solution of XAI [50]. Holzinger et al. present research on explainable AI in the medical domain [36]. They argue that benefits can be obtained from AI algorithms, but only in case the results are explainable and can be argued. They summarise that hybrid distributional models which map sparse graph-based information to dense vectors of information are suitable to provide context by linking this information to lexical sources and knowledge bases.
3 What is Explainability of AI

According to Linardatos et al., explainability or interpretability of AI algorithms depends on four dimensions [45]:

– Local vs global,
– data types that are processed by the algorithm,
– the purpose of interpretability, i.e. when and how should the model be explained, and
– the generalisation of the interpretation, i.e. can the explanation be applied to individual models or to any model.

Furthermore, several works address the issue of target audience [66], which should also be taken into consideration. These dimensions are shown in Figure 1. A trend that is observed by every work surveyed in this paper is the relationship between complexity of algorithms and difficulty of explainability. Models based on Decision Trees, such as Random Forests [21] and XGBoost [17] not only perform well in praxis [25], but also allow for a good understanding of global explainability. That means the model provides information about the relevance of its learned features. Furthermore, the splits allow insight into the creation of output. In contrast, Deep Neural Networks (DNNs) create complex models that cannot easily be understood by humans. In case of image and video processing, methods are available to highlight the areas in an image that induce the highest neuron output and thus are most relevant for the algorithmic output [60]. This method cannot be applied as easily to abstract, high-dimensional information which is inherently difficult to interpret for humans. Several works use contextual

Fig. 1. Explainability Goals According to Linardatos et. al [45], Extended
information as well as knowledge bases that provide additional information and allow the generation and connection of the original algorithm with algorithms used to explain the outcome \cite{[15],[28]}. This can be closely combined with understanding of how humans explain decisions and understand explanations \cite{[65]}.

This question is closely coupled to the target audience of explanations: while data scientists and engineers are interested in model performance, users might be more interested in the base information that led to a certain outcome. In domain-specific applications, the explainability might be used to increase customer satisfaction and thus revenue \cite{[15]}, meaning the business operators need to understand not only what customers desire, but why. In medical applications, compliance and liability play important roles \cite{[38],[62],[60]}, meaning someone has to be responsible for a decision. Consequently, a medical professional has to be able to obtain information of the root cause of an automated decision. In social and judicial applications, fairness independent of human-induced bias is relevant as well as argumentation regarding the reasons for conclusions \cite{[26],[1]}.

This section shows that explainability is a broad and rather abstract concept, once one is trying to implement it. Not only does the data and algorithm have a strong influence on the methods of explainability that are possible in the first place, also the goal and audience of an explanation are relevant. The domains and consequently the goals of explainability are discussed in the next section.

4 Domains for Explainability

It is noteworthy that there is distinction in related work, as discussed in Section \cite{[2]} regarding the use cases discussed: The first part of papers present solutions, and sometimes challenges, to enhance explainability of certain algorithms or types of algorithms. At the same time, the second part of papers discusses requirements, challenges and solutions of certain fields or domains, without specific algorithms in mind. Furthermore, several papers address XAI as a means for improved outcomes and stakeholder or user acceptance, while others solely address technical challenges. For a holistic explainability architecture, those have to be merged. Generally, the two different ways of approaching explainability show in this survey. Domain experts have a concrete challenge that can be solved, or improved, with AI methods. Alternatively, an AI method is already solving the challenge and the domain expert needs reasoning for the model, be it to appease stakeholders or to increase customer satisfaction. Such approaches often use knowledge bases of methods to solve the issue without AI.

The other approach is from machine learning and AI experts who aim to make their models more transparent. Often, this is based in the need to understand the model in order to increase performance, resulting in explainability by accuracy and sensitivity metrics. Such information is difficult to interpret by non-experts and thus not suited for explainability for users. In summary, the different domains for explainability highlight the need for distinction in the solution. In recommender systems for e-commerce, a wrong recommendation will
not have severe consequences, in stark contrast to recommendation systems for medical examination. Understanding models to fine-tune them is a valid task for data scientists and machine learning experts, while an ontological explanation similar to human reasoning is necessary for integration of AI models into socio-economic and organisational solutions. While it is a highly interesting concept, a holistic solution to explainability does not seem likely.

5 Conclusion

A large body of research regarding XAI has been presented in this work. This body of research spans several domains, including medicine and healthcare, commerce, criminal and social sciences, and recommender systems. While highlighting that all of these domains face similar challenges, the mass of surveys and taxonomies discussed in this work also show the wide span of requirements. Additionally, the technique of explainability strongly depends on the employed AI algorithm. Simpler algorithms, for example tree-based ones, can be understood by humans relatively easy as the information of the decision can be extracted directly from the model in a semantically understandable fashion. More complex algorithms, such as DNNs prove to be more difficult. If the data they analyse can be understood intuitively by humans, as is the case in image processing, the neuronal activity can be displayed. However, in complex and unstructured data, such as high dimensional tables, highlighting of the values does not provide humans with an understanding of the reasoning. Here, knowledge bases to map against or ontological translations of the results are required in order to provide an understanding.

AI-based recommender systems are bound to drastically increase performance and quality of services they provide. Due to the variety of said services, individual explanation frameworks will be applied. Furthermore, recipient and reason for wanting an explanation play an important role in choosing an explanation framework. In the future, AI systems might increasingly make decisions autonomously, i.e. without supervision and approval of a human operator. Such applications will require strict regulation and liability frameworks to ensure that AI methods perform in an expected and sound manner.

Acknowledgement

This work has been supported by the Federal Ministry of Education and Research (BMBF) of the Federal Republic of Germany (Foerderkennzeichen 19I21028R, WaVe) and the Investment and Structure Bank (ISB) Rhineland Palatinate (Foerderkennzeichen P1SZ26, InnoTop). The authors alone are responsible for the content of this paper.
References

1. Abdollahi, B., Nasraoui, O.: Transparency in fair machine learning: the case of explainable recommender systems. In: Human and machine learning, pp. 21–35. Springer (2018)
2. Adadi, A., Berrada, M.: Peeking inside the black-box: a survey on explainable artificial intelligence (xai). IEEE access 6, 52138–52160 (2018)
3. Ai, Q., Azizi, V., Chen, X., Zhang, Y.: Learning heterogeneous knowledge base embeddings for explainable recommendation. Algorithms 11(9), 137 (2018)
4. Amann, J., Blasimme, A., Vayena, E., Frey, D., Madai, V.I.: Explainability for artificial intelligence in healthcare: a multidisciplinary perspective. BMC Medical Informatics and Decision Making 20(1), 1–9 (2020)
5. Ammar, N., Shaban-Nejad, A.: Explainable artificial intelligence recommendation system by leveraging the semantics of adverse childhood experiences: Proof-of-concept prototype development. JMIR Medical Informatics 8(11), e18752 (2020)
6. Angelov, P.P., Soares, E.A., Jiang, R., Arnold, N.I., Atkinson, P.M.: Explainable artificial intelligence: an analytical review. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery 11(5), e1424 (2021)
7. Arya, V., Bellamy, R.K., Chen, P.Y., Dhurandhar, A., Hind, M., Hoffman, S.C., Houde, S., Liao, Q.V., Luss, R., Mojsilović, A.: One explanation does not fit all: A toolkit and taxonomy of AI explainability techniques. arXiv preprint arXiv:1909.03012 (2019)
8. Arya, V., Bellamy, R.K., Chen, P.Y., Dhurandhar, A., Hind, M., Hoffman, S.C., Houde, S., Liao, Q.V., Luss, R., Mojsilovic, A.: AI explainability 360: An extensible toolkit for understanding data and machine learning models. J. Mach. Learn. Res. 21(130), 1–6 (2020)
9. Barredo Arrieta, A., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., García, S., Gil-López, S., Molina, D., Benjamins, R.: Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. Information fusion 58, 82–115 (2020)
10. Beaudouin, V., Bloch, I., Bounie, D., Clémentelon, S., d’Alché Buc, F., Eagan, J., Maxwell, W., Mozharovskyi, P., Parekh, J.: Flexible and context-specific AI explainability: a multidisciplinary approach. Available at SSRN 3559477 (2020)
11. Belle, V., Papantonis, I.: Principles and practice of explainable machine learning. Frontiers in big Data p. 39 (2021)
12. Bellini, V., Schiavone, A., Di Noia, T., Ragone, A., Di Sciascio, E.: Knowledge-aware autoencoders for explainable recommender systems. In: Proceedings of the 3rd Workshop on Deep Learning for Recommender Systems. pp. 24–31 (2018)
13. Bhatt, U., Xiang, A., Sharma, S., Weller, A., Taly, A., Jia, Y., Ghosh, J., Puri, R., Moura, J.M., Eckersley, P.: Explainable machine learning in deployment. In: Proceedings of the 2020 conference on fairness, accountability, and transparency. pp. 648–657 (2020)
14. Cao, L.: Ai in finance: Challenges, techniques, and opportunities. ACM Computing Surveys (CSUR) 55(3), 1–38 (2022)
15. Caro-Martínez, M., Jiménez-Díaz, G., Recio-García, J.A.: Conceptual modeling of explainable recommender systems: an ontological formalization to guide their design and development. Journal of Artificial Intelligence Research 71, 557–589 (2021)
16. Cashmore, M., Collins, A., Krarup, B., Krivic, S., Magazzeni, D., Smith, D.: Towards explainable AI planning as a service. arXiv preprint arXiv:1908.05059 (2019)
17. Chen, T., Guestrin, C.: Xgboost: A scalable tree boosting system. In: Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining. pp. 785–794 (2016)
18. Chen, X., Zhang, Y., Qin, Z.: Dynamic explainable recommendation based on neural attentive models. In: Proceedings of the AAAI Conference on Artificial Intelligence. vol. 33, pp. 53–60 (2019)
19. Coope, M.: Artificial intelligence, responsibility attribution, and a relational justification of explainability. Science and engineering ethics 26(4), 2051–2068 (2020)
20. Confalonieri, R., Coba, L., Wagner, B., Besold, T.R.: A historical perspective of explainable artificial intelligence. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery 11(1), e1391 (2020)
21. Cutler, A., Cutler, D.R., Stevens, J.R.: Random forests. In: Ensemble machine learning, pp. 157–175. Springer (2012)
22. Duque-Antón, M., Kunz, D., Ruber, B.: Channel assignment for cellular radio using simulated annealing. IEEE Transactions on Vehicular Technology 42(1), 14–21 (1993)
23. Duque Anton, S., Kanoo, S., Fraunholz, D., Schotten, H.D.: Evaluation of machine learning-based anomaly detection algorithms on an industrial modbus/tcp data set. In: Proceedings of the 13th international conference on availability, reliability and security. pp. 1–9 (2018)
24. Duque Anton, S.D.: Anomaly Detection in Industry. Verlag Dr. Hut (2021)
25. Duque Anton, S.D., Sinha, S., Schotten, H.D.: Anomaly-based intrusion detection in industrial data with SVM and random forests. In: 2019 International conference on software, telecommunications and computer networks (SoftCOM). pp. 1–6. IEEE (2019)
26. Ehsan, U., Liao, Q.V., Muller, M., Riedl, M.O., Weisz, J.D.: Expanding explainability: towards social transparency in AI systems. In: Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems. pp. 1–19 (2021)
27. Ehsan, U., Liao, Q.V., Muller, M., Riedl, M.O., Weisz, J.D.: Expanding explainability: towards social transparency in AI systems. In: Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems. pp. 1–19 (2021)
28. Gade, K., Geyik, S.C., Kenthapadi, K., Mithal, V., Taly, A.: Explainable AI in industry. In: Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining. pp. 3203–3204 (2019)
29. Goebel, R., Chander, A., Holzinger, K., Lecue, F., Akata, Z., Stumpf, S., Kieseberg, P., Holzinger, A.: Explainable AI: the new 42? In: International cross-domain conference for machine learning and knowledge extraction. pp. 295–303. Springer (2018)
30. Gunning, D., Stefik, M., Choi, J., Miller, T., Stumpf, S., Yang, G.Z.: XAI—explainable artificial intelligence. Science Robotics 4(36), eaay7120 (2019)
31. Hagras, H.: Toward human-understandable, explainable AI. Computer 51(9), 28–36 (2018)
32. Hamet, P., Tremblay, J.: Artificial intelligence in medicine. Metabolism 69, S36–S40 (2017)
33. Hoffman, R.R., Mueller, S.T., Klein, G., Litman, J.: Metrics for explainable AI: Challenges and prospects. arXiv preprint arXiv:1812.04608 (2018)
34. Hois, J., Theofanou-Fuelbier, D., Junk, A.J.: How to achieve explainability and transparency in human AI interaction. In: International Conference on Human-Computer Interaction. pp. 177–183. Springer (2019)
35. Holzinger, A.: From machine learning to explainable AI. In: 2018 world symposium on digital intelligence for systems and machines (DISA). pp. 55–66. IEEE (2018)
36. Holzinger, A., Biemann, C., Pattichis, C.S., Kell, D.B.: What do we need to build explainable AI systems for the medical domain? arXiv preprint arXiv:1712.09923 (2017)
37. Holzinger, A., Langs, G., Denk, H., Zatloukal, K., Müller, H.: Causability and explainability of artificial intelligence in medicine. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery 9(4), e1312 (2019)
38. Holzinger, A.T., Müller, H.: Toward human–AI interfaces to support explainability and causability in medical AI. Computer 54(10), 78–86 (2021)
39. Jiang, W., Duque Anton, S., Schotten, H.D.: Intelligence slicing: A unified framework to integrate artificial intelligence into 5g networks. In: 2019 12th IFIP Wireless and Mobile Networking Conference (WMNC). pp. 227–232. IEEE (2019)
40. Jiang, W., Strufe, M., Schotten, H.D.: Intelligent network management for 5g systems: The selinet approach. In: 2017 European conference on networks and communications (EuCNC). pp. 1–5. IEEE (2017)
41. Kailkhura, B., Gallagher, B., Kim, S., Hiszpanski, A., Han, T.: Reliable and explainable machine-learning methods for accelerated material discovery. npj Computational Materials 5(1), 1–9 (2019)
42. Keneni, B.M., Kaur, D., Al Bataineh, A., Devabhaktuni, V.K., Javaid, A.Y., Zaientz, J.D., Marinier, R.P.: Evolving rule-based explainable artificial intelligence for unmanned aerial vehicles. IEEE Access 7, 17001–17016 (2019)
43. Kuhn, R., Kacker, R.: An application of combinatorial methods for explainability in artificial intelligence and machine learning (draft). Tech. rep., National Institute of Standards and Technology (2019)
44. Liang, Q., Zheng, X., Wang, Y., Zhu, M.: O3ERS: An explainable recommendation system with online learning, online recommendation, and online explanation. Information Sciences 562, 94–115 (2021)
45. Linardatos, P., Papastefanopoulos, V., Kotsiantis, S.: Explainable AI: A review of machine learning interpretability methods. Entropy 23(1), 18 (2020)
46. Lundberg, S.M., Erion, G., Chen, H., DeGrave, A., Prutkin, J.M., Nair, B., Katz, R., Himmelfarb, J., Bansal, N., Lee, S.I.: From local explanations to global understanding with explainable AI for trees. Nature machine intelligence 2(1), 56–67 (2020)
47. Mohseni, S., Zarei, N., Ragan, E.D.: A multidisciplinary survey and framework for design and evaluation of explainable AI systems. ACM Transactions on Interactive Intelligent Systems (TIIS) 11(3-4), 1–45 (2021)
48. Neugebauer, S., Rippitsch, L., Sobieczky, F., Geiß, M.: Explainability of predictions based on psychological profiling. Procedia Computer Science 180, 1003–1012 (2021)
49. Ploug, T., Holm, S.: The four dimensions of contestable AI diagnostics—a patient-centric approach to explainable ai. Artificial Intelligence in Medicine 107, 101901 (2020)
50. Preece, A.: Asking ‘why’in ai: Explainability of intelligent systems—perspectives and challenges. Intelligent Systems in Accounting, Finance and Management 25(2), 63–72 (2018)
51. Qian, K., Zhang, Z., Yamamoto, Y., Schuller, B.W.: Artificial intelligence internet of things for the elderly: From assisted living to health-care monitoring. IEEE Signal Processing Magazine 38(4), 78–88 (2021)
52. Reddy, S.: Explainability and artificial intelligence in medicine. The Lancet Digital Health 4(4), e214–e215 (2022)
53. Roscher, R., Bohn, B., Duarte, M.F., Garcke, J.: Explainable machine learning for scientific insights and discoveries. Ieee Access 8, 42200–42216 (2020)
54. Samek, W., Montavon, G., Vedaldi, A., Hansen, L.K., Müller, K.R.: Explainable AI: interpreting, explaining and visualizing deep learning, vol. 11700. Springer Nature (2019)
55. Sands, T.: Development of deterministic artificial intelligence for unmanned underwater vehicles (UUV). Journal of Marine Science and Engineering 8(8), 578 (2020)
56. Schutera, M., Goby, N., Neumann, D., Reischl, M.: Transfer learning versus multi-agent learning regarding distributed decision-making in highway traffic. arXiv preprint arXiv:1810.08515 (2018)
57. Schutera, M., Hussein, M., Abhau, J., Mikut, R., Reischl, M.: Night-to-day: Online image-to-image translation for object detection within autonomous driving by night. IEEE Transactions on Intelligent Vehicles 6(3), 480–489 (2020)
58. Shen, X., Gao, J., Wu, W., Lyu, K., Li, M., Zhuang, W., Li, X., Rao, J.: Ai-assisted network-slicing based next-generation wireless networks. IEEE Open Journal of Vehicular Technology 1, 45–66 (2020)
59. Shin, D.: The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. International Journal of Human-Computer Studies 146, 102551 (2021)
60. Singh, A., Sengupta, S., Lakshminarayanan, V.: Explainable deep learning models in medical image analysis. Journal of Imaging 6(6), 52 (2020)
61. Sun, W., Liu, J., Yue, Y.: Ai-enhanced offloading in edge computing: When machine learning meets industrial iot. IEEE Network 33(5), 68–74 (2019)
62. Tjoa, E., Guan, C.: A survey on explainable artificial intelligence (XAI): Toward medical XAI. IEEE transactions on neural networks and learning systems 32(11), 4793–4813 (2020)
63. Tonekaboni, S., Joshi, S., McCradden, M.D., Goldenberg, A.: What clinicians want: contextualizing explainable machine learning for clinical end use. In: Machine learning for healthcare conference. pp. 359–380. PMLR (2019)
64. Vilone, G., Longo, L.: Notions of explainability and evaluation approaches for explainable artificial intelligence. Information Fusion 76, 89–106 (2021), https://www.sciencedirect.com/science/article/pii/S1566253521001093
65. Wang, D., Yang, Q., Abdul, A., Lim, B.Y.: Designing theory-driven user-centric explainable AI. In: Proceedings of the 2019 CHI conference on human factors in computing systems. pp. 1–15 (2019)
66. Zhang, Y., Chen, X.: Explainable recommendation: A survey and new perspectives. Foundations and Trends® in Information Retrieval 14(1), 1–101 (2020)
### Table 1. Overview of Related Works

| Year | Work | Domain                  | Topic of Explainability                                                                 |
|------|------|-------------------------|----------------------------------------------------------------------------------------|
| 2022 | 52   | Medicine                | Accuracy vs. explainability                                                             |
| 2021 | 48   | Product & company success | Before and after model comparison                                                        |
| 2021 | 64   | Survey                  | Comparison of methods aimed at human-based understanding and objective metrics            |
| 2021 | 15   | e-commerce              | Ontological model                                                                      |
| 2021 | 64   | Recommendation systems   | Leverage of recommendation and explanation                                               |
| 2021 | 44   | Medical domain          | “Mapping of explainability with causability”                                           |
| 2021 | 53   | Socio-economic decisions | Social transparency as guidelines for decision making                                    |
| 2021 | 47   | Survey                  | Global vs. local, accuracy vs. explainability                                           |
| 2021 | 17   | Survey                  | Multi-domain model                                                                    |
| 2021 | 11   | Data science             | Survey based on stakeholder use-case                                                     |
| 2021 | 79   | Product recommendation  | Relationship of causability and explainability                                          |
| 2020 | 60   | Medicine                | Explainable image processing                                                            |
| 2020 | 10   | Survey                  | Fairness of the model                                                                  |
| 2020 | 10   | Tree-based algorithms   | Game theory-based approach                                                              |
| 2020 | 10   | Medicine                | Contestability                                                                        |
| 2020 | 57   | Data Science             | Toolkit-framework combining state of the art methods                                     |
| 2020 | 55   | Survey & Taxonomy        | Survey                                                                                  |
| 2020 | 42   | Medicine                | Survey                                                                                  |
| 2020 | 58   | Natural sciences         | Survey                                                                                  |
| 2020 | 10   | Multidisciplinary        | Three-step framework                                                                   |
| 2020 | 10   | General                 | Responsibility of AI algorithms                                                         |
| 2020 | 10   | Survey                  | Stakeholder-driven explainability survey                                                |
| 2020 | 10   | Mental health evaluation | Ontological agent                                                                       |
| 2020 | 50   | Survey                  | Survey                                                                                  |
| 2020 | 40   | Survey                  | Survey                                                                                  |
| 2019 | 15   | Medicine                | Multidisciplinary survey of requirements in explainability                               |
| 2019 | 15   | User product recommendation | Dynamic preference monitoring with neural networks                                     |
| 2019 | 15   | Proof of Concept         | Fault location in combinatorial testing                                                 |
| 2019 | 11   | Material sciences        | Analogy creation and feature importance                                                 |
| 2019 | 63   | Medicine                | Domain appropriate representation, potential accountability, and consistency            |
| 2019 | 65   | General                 | Psychology-based theoretical cognitive framework                                        |
| 2019 | 10   | Industrial planning      | Contrastive explanations                                                                |
| 2019 | 14   | Human-centric decision making | Context-based                                                                          |
| 2019 | 25   | Survey for industrial application | Survey                                                                                 |
| 2019 | 14   | Survey                  | Several                                                                                 |
| 2019 | 10   | Survey                  | Survey                                                                                  |
| 2019 | 14   | Medicine                | Definition of causability and explainability                                           |
| 2018 | 12   | Product recommendation  | Knowledge-base embedding representation                                                 |
| 2018 | 12   | (Movie) recommendations  | Knowledge graphs                                                                        |
| 2018 | 13   | User acceptance          | Survey                                                                                  |
| 2018 | 11   | Survey                  | Rule-based decisions & labels                                                            |
| 2018 | 1    | Survey                  | Survey                                                                                  |
| 2018 | 11   | Health, education, justice, survey | Survey                                                                                  |
| 2018 | 10   | Position paper           | Context-adaptive procedures                                                              |
| 2018 | 29   | Position paper           | Bridging cognitive valley with graph information                                         |
| 2018 | 50   | Survey                  | Taxonomy for XAI                                                                        |
| 2017 | 10   | Medicine                | Hybrid distributional models                                                            |