A Systematic Literature Review on Explainability for Machine/Deep Learning-based Software Engineering Research

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The online appendix introduces the review methodology of our main paper, which is outlined as follows. Appendix A.1 describes the search strategy to identify relevant studies. Appendix A.2 presents the procedure to select the primary studies that provide direct evidence about the research questions. Appendix A.3 provides the basic review results, including the publication statistics over years and distribution of publications in various venues. Appendix A.4 discusses the possible threats to validity in our review process.

CCS Concepts: • **General and reference** → *Surveys and overviews*; • **Computing methodologies** → *Neural networks*; *Artificial intelligence*; • **Software and its engineering** → *Software development techniques.*

Additional Key Words and Phrases: Explainable AI, XAI, interpretability, neural networks, survey

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A REVIEW METHODOLOGY

A.1 Search Strategy

As shown in Figure 1, following the standardized practice within the field of SE [5], our first step involves identifying primary studies to enhance our ability to address the formulated RQs effectively. Given that the DL revolution – triggered by AlexNet in 2012 – has transformed AI research and became the catalyst for the ML/DL boom in all fields including SE, we chose a 13-year period of January 1st, 2012, to December 31st, 2024, to collect the literature related to XAI4SE. Next, we identified the top peer-review and influential conference and journal venues in the domains of

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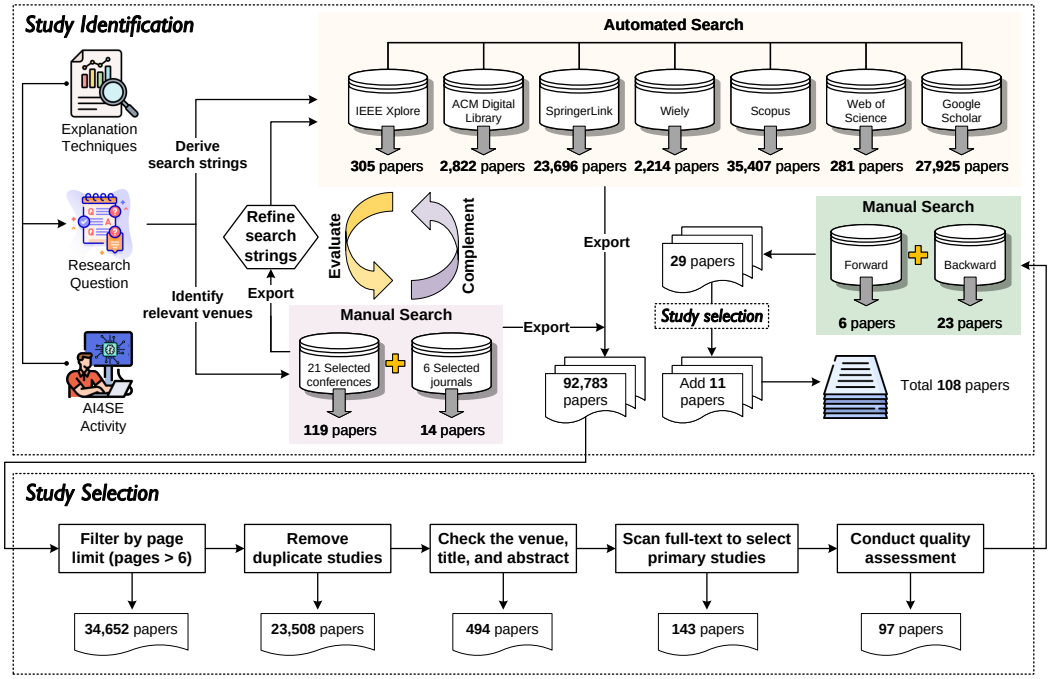


Fig. 1. Study identification and selection process.

SE and Programming Languages (PL), as outlined in Table 1. In total, we included 16 conferences (ICSE, ASE, ESEC/FSE, ICSME, ICPC, RE, ESEM, ISSTA, MSR, SANER, ISSRE, APSEC, COMPSAC, QRS, OOPSLA, PLDI) and six journals (TSE, TOSEM, EMSE, JSS, IST, ASEJ). We chose to include PL venues in our study given the frequent overlap of SE and PL research. Furthermore, we also include five top conferences (AAAI, ICML, ICLR, NeurIPS, IJCAI) that centered on machine learning (ML) and deep learning (DL) as these conferences might feature papers applying ML and DL techniques to SE tasks.

Apart from manually searching primary studies from top-tier venues, we also retrieved relevant papers from five popular digital libraries, including IEEE Xplore[1], ACM Digital Library[2], SpringerLink[3], Wiely[4], and Scopus[5], and two of the most popular research citation engines, Web of Science[6] and Google Scholar[7], based on the search string (listed in Table 2) assembled from a group of topic-related keywords summarized from manually collected papers. As shown in Table 3, we collected a total of 92,783 relevant studies with the automatic search from these seven electronic databases.

[1]https://ieeexplore.ieee.org
[2]https://dl.acm.org
[3]https://link.springer.com
[4]https://onlinelibrary.wiley.com
[5]https://www.scopus.com
[6]https://www.webofscience.com
[7]https://scholar.google.com

Table 1. Publication Venues for Manual Search

Venue	Acronym	Full name
Conference	ICSE	IEEE/ACM International Conference on Software Engineering
	ASE	IEEE/ACM International Conference Automated Software Engineering
	ESEC/FSE*	ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering
	ICSME	IEEE International Conference on Software Maintenance and Evolution
	ICPC	IEEE International Conference on Program Comprehension
	RE	IEEE International Conference on Requirements Engineering
	ESEM	ACM/IEEE International Symposium on Empirical Software Engineering and Measurement
	ISSTA	ACM SIGSOFT International Symposium on Software Testing and Analysis
	MSR	IEEE Working Conference on Mining Software Repositories
	SANER	IEEE International Conference on Software Analysis, Evolution and Reengineering
	ISSRE	IEEE International Symposium on Software Reliability
	APSEC	Asia-Pacific Software Engineering Conference
	COMPSAC	IEEE International Computer Software and Applications Conference
	QRS	IEEE International Conference on Software Quality, Reliability and Security
	OOPSLA	ACM SIGPLAN International Conference on Object-oriented Programming, Systems, Languages, and Applications
	PLDI	ACM SIGPLAN Conference on Programming Language Design and Implementation
	AAAI	AAAI Conference on Artificial Intelligence
	ICML	International Conference on Machine Learning
	ICLR	International Conference on Learning Representations
	NeurIPS	Annual Conference on Neural Information Processing Systems
	IJCAI	International Joint Conference on Artificial Intelligence
Journal	TSE	IEEE Transactions on Software Engineering
	TOSEM	ACM Transactions on Software Engineering and Methodology
	EMSE	Empirical Software Engineering
	JSS	Journal of Systems and Software
	IST	Information and Software Technology
	ASEJ	Automated Software Engineering

* The conference name is changed to ACM International Conference on the Foundations of Software Engineering (FSE) since 2024.

A.2 Study Selection

A.2.1 Inclusion and Exclusion Criteria. After paper collection, we performed a relevance assessment according to the following inclusion and exclusion criteria:

- ✓ *The paper must be written in English.*
- ✓ *The paper must be a peer-reviewed full research paper published in a conference proceeding or a journal.*
- ✓ *The paper must have an accessible full text.*
- ✓ *The paper must adopt ML/DL techniques to address SE problems.*
- ✗ *The paper has less than 6 pages.*
- ✗ *Books, keynote records, non-published manuscripts, and grey literature are dropped.*
- ✗ *The paper is a literature review or survey.*
- ✗ *The paper is not a conference paper that has been extended as a journal paper.*
- ✗ *The paper uses SE approaches to contribute to ML/DL systems.*
- ✗ *The studies that do not apply XAI techniques on SE tasks are ruled out.*
- ✗ *The studies where explainability is discussed as an idea or part of the future work are excluded.*

Table 2. Search Keywords

Group	Keywords
1	*"Machine Learn*"* OR *"Deep Learning"* OR *"Neural Network?"* OR *"Reinforcement Learning"*
2	*"Explainable"* OR *"Interpretable"* OR *"Explainability"* OR *"Interpretability"*
3	*"Software Engineering"* OR *"Software Analytics"* OR *"Software Mainten*"* OR *"Software Evolution"* OR *"Software Test*"* OR *"Software Requirement?"* OR *"Software Develop*"* OR *"Project Management"* OR *"Software Design*"* OR *"Dependability"* OR *"Security"* OR *"Reliability"*
4	*"Code Representation"* OR *"Code Generation"* OR *"Code Comment Generation"* OR *"Code Search"* OR *"Code Localization"* OR *"Code Completion"* OR *"Code Summarization"* OR *"Method Name Generation"* OR *"Bug"* OR *"Fault"* OR *"Vulnerability"* OR *"Defect"* OR *"Test Case"* OR *"Program Analysis"* OR *"Program Repair"* OR *"Clone Detection"* OR *"Code Smell"* OR *"SATD Detection"* OR *"Compile"* OR *"Code Review"* OR *"Code Classification"* OR *"Code Change"* OR *"Incident Detection"* OR *"Effort Cost Prediction"* OR *"GitHub"* OR *"StackOverflow"* OR *"Developer"*

* is a wildcard used to match zero or more characters.
? is another wildcard used to match a single character.

Table 3. Summary of the Process of Study Search and Selection

Data Source	# Studies
IEEE Xplore	305
ACM Digital Library	2,822
SpringerLink	23,696
Wiely	2,214
Scopus	35,407
Web of Science	281
Google Scholar	27,925
Merge	92,783
Filtering studies less than 6 pages	34,652
Removing duplicated studies	23,508
Excluding primary studies based on venue, title, and abstract	494
Excluding primary studies based on full text	143
After Quality Assessment	97
After Forward & Backward Snowballing	126
Final	108

In particular, by literature filtering and deduplication (exclusion criteria 1), the total number of included papers was reduced to 23,508. After the first two authors manually examined the venue, title, and abstracts of the papers, the total number of included papers declined substantially to 494. Any ambiguous papers would be forwarded to the fourth and 11th authors who were experienced in the fields of SE and XAI research to conduct a secondary review. In addition, books, keynote records, non-published manuscripts, grey literature, SLRs/surveys, and conference versions of extended papers were also discarded in this phase (exclusion criteria 2-4). The SE4AI papers [1], which used SE approaches to contribute to ML/DL systems were also not considered (exclusion

Table 4. Checklist of Quality Assessment Criteria for Explainability Studies in AI4SE

No.	Quality Assessment Criteria
QAC_1	Is the impact of the proposed approach (or empirical/case study) on the AI4SE community clearly stated?
QAC_2	Are the contributions of the study clearly claimed?
QAC_3	Does the study provide a clear description of the workflow and implementation of the proposed approach?
QAC_4	Are the experiment details, including datasets, baselines, and evaluation metrics, clearly described?
QAC_5	Do the findings drawn from the experiments strongly substantiate the arguments presented in the study?

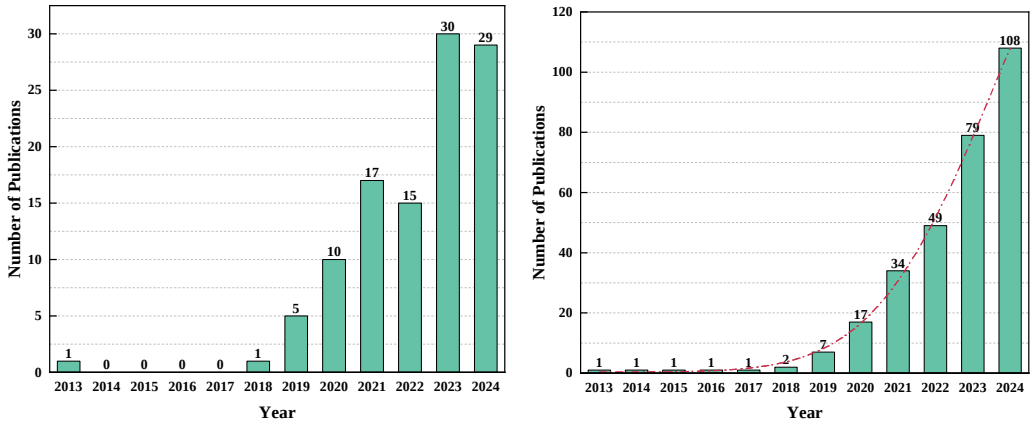
Table 5. Extracted Data Items and Related Research Questions

RQ	Data Item
RQ_1	The SE task that an XAI4SE approach tries to solve
RQ_1	The SE activity in which each SE task belongs
RQ_1	Publication type of each primary study (i.e., new technique, empirical study, or case study)
RQ_2	XAI technique employed by each study
RQ_2	Explanation format
RQ_3	The adopted baseline approaches
RQ_3	Benchmark dataset name
RQ_3	Presence/absence of replication package
RQ_3	What metrics are used to evaluate the XAI techniques

criteria 5) because our SLR focused exclusively on the explainability of AI4SE models. Furthermore, we ruled out studies that did not apply XAI techniques on SE tasks, or just discussed explainability as an idea or future work (exclusion criteria 6 & 7). In the fourth phase, we reviewed the full texts of the papers (inclusion criteria 3), identifying 143 primary studies directly relevant to our research topic.

A.2.2 Quality Assessment. To prevent biases introduced by low-quality studies, we formulated five **Quality Assessment Criteria (QAC)**, given in Table 4, to evaluate the 143 included studies. The quality assessment process was piloted by the first and second authors, involving 30 randomly selected primary studies. We adopted pairwise inter-rater reliability with Cohen's Kappa statistic to measure the consistency of the markings. For any case that they did not reach a consensus after open discussions, the fourth and 11th authors (domain experts experienced in SE and XAI) were consulted as tie-breakers. Within two iterations, the Cohen's Kappa coefficient was successfully raised from *moderate* (0.58) to *almost perfect agreement* (0.84). Then, an assessment was performed for the remaining 113 primary studies. After quality assessment, a final set of 97 high-quality papers was reserved.

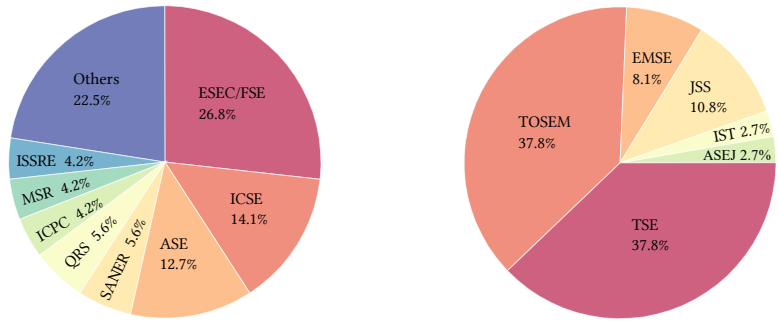
A.2.3 Forward and Backward Snowballing. To avoid omitting any possibly relevant work during our manual and automated search process, we also performed lightweight backward and forward snowballing, i.e., basically examining the research referenced in each of our selected primary studies, as well as the publications that subsequently referred to these studies, on the references and the citations of 97 high-quality papers. As a supplement, we gathered 29 more papers, and conducted the complete study selection process again, including filtering, deduplication, and quality assessment, and obtained 11 additional papers.



(a) Distribution of publications per year.

(b) Cumulative publication trend over years.

Fig. 2. Publication statistics over years.



(a) Distribution of publications in various conferences.

(b) Distribution of publications in various journals.

Fig. 3. Distribution of selected papers in different publication venues.

A.3 Data Extraction and Analysis

Based on the collected 108 primary studies, we extracted the essential data items used to answer three main RQs. In Table 5, we outline the details information extracted and gathered from 108 primary studies. The column labeled "Data Item" enumerates the relevant data items extracted from each primary study, while the column "RQ" specifies the corresponding research question. In order to mitigate errors during data extraction, the first two authors working together on extracting these data items from the primary studies. Then, the fifth author verified the extracted data results.

Figure 2a presents the distribution of selected primary studies in each year. The first XAI4SE study we found was published in 2013. After that, there was a 4-year research gap, ranging from 2014 to 2017. The enthusiasm for investigating the explainability on AI4SE models has steadily risen since 2018, and reaches its peak in recent two years, comprising 54.6% of the total publications. Figure 2b illustrates the cumulative publication trend over years. It is observable that the slope of the curve fitting the distribution experiences a significant increase between 2019 and 2024. This pronounced upward trend indicates a burgeoning research interest in the field of XAI4SE.

We also analyzed the publication trend of primary studies in selected conferences and journal venues, respectively. As shown in Figure 3a, ESEC/FSE stands out as the predominant conference venues favored by XAI4SE studies, with a contribution of 26.8% of the total. Other venues making noteworthy contributions include ICSE (14.1%), ASE (12.7%), and SANER/QRS (5.6%). Figure 3b shows the distribution of primary papers published in different journal venues. It can be seen that 75.6% of relevant papers were published in TSE and TOSEM, which indicates a booming trend of XAI4SE research in top-tier SE journals in the past few years.

A.4 Threats to Validity

Study Collection Omission. Our review has some potential limitations, and one of them is the risk of inadvertently excluding relevant studies during the literature search and selection phase. The incomplete summarization of keywords related to SE tasks and the varied use of terminology for explainability across studies may have led to our search criteria overlooking relevant research that ought to have been incorporated into our SLR. To address this concern, we first manually selected 27 top-tier SE & AI venues suggested by previous surveys on AI4SE research [2–4], and extracted relatively comprehensive and standard keywords for SE tasks and XAI techniques. With these search strings, we further augmented our search results by combining automated search with forward-backward snowballing.

Data Extraction Bias. Another potential limitation is data extraction bias. Certain discrepancies arose inevitably when extracting related content and classifying the data items in Table 5. To mitigate the bias in data extraction phase to the validity of our findings, we invited two practitioners, the fourth and 11th authors, to conduct a secondary review of controversial data items that unable to reach consensus on classification. Both of them have more than 10 years of experience in the field of SE and XAI.

By applying these countermeasures, we strive to guarantee the comprehensiveness of the selected papers and the accuracy of the data items, thereby enhancing the reliability of our findings.

REFERENCES

[1] Saleema Amershi, Andrew Begel, Christian Bird, Robert DeLine, Harald C. Gall, Ece Kamar, Nachiappan Nagappan, Besmira Nushi, and Thomas Zimmermann. 2019. Software Engineering for Machine Learning: A Case Study. In *Proceedings of the 41st International Conference on Software Engineering: Software Engineering in Practice (ICSE-SEIP)*. IEEE/ACM, 291–300.

[2] Simin Wang, Liguo Huang, Amiao Gao, Jidong Ge, Tengfei Zhang, Haitao Feng, Ishna Satyarth, Ming Li, He Zhang, and Vincent Ng. 2023. Machine/Deep Learning for Software Engineering: A Systematic Literature Review. *IEEE Trans. Software Eng.* 49, 3 (2023), 1188–1231.

[3] Cody Watson, Nathan Cooper, David Nader-Palacio, Kevin Moran, and Denys Poshyvanyk. 2022. A Systematic Literature Review on the Use of Deep Learning in Software Engineering Research. *ACM Trans. Softw. Eng. Methodol.* 31, 2 (2022), 32:1–32:58.

[4] Yanming Yang, Xin Xia, David Lo, and John C. Grundy. 2022. A Survey on Deep Learning for Software Engineering. *ACM Comput. Surv.* 54, 10s (2022), 206:1–206:73.

[5] He Zhang, Muhammad Ali Babar, and Paolo Tell. 2011. Identifying Relevant Studies in Software Engineering. *Inf. Softw. Technol.* 53, 6 (2011), 625–637.