Physics-Informed Learning Machines Literature

518 Citations from my *Physics of Data* Obsidian vault

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Citation Bibliography - PhysicsOfData Vault

Executive Summary

Total Citations Found: 518

Table 1: Citation Categorization Summary

Category	Number of Citations	Percentage
Scientific Machine Learning (Core)	462	89.2%
Supporting Papers	56	10.8%

Bibliometric Analysis

Table 2: Temporal and Repository Coverage

Metric	Value
Publication Year Range	1915 - 2025
Median Publication Year	2019
Most Productive Decade	2020s (246 citations)
Citations with Git Repositories	158
Repository Coverage Rate	30.5%
Citations with Reference Counts	494
Reference Data Coverage	95.4%
Average References per Citation	61
Citations with KDensity Scores	518
KDensity Coverage Rate	100%

Table 3: Quality and Impact Metrics

Metric	Value
Avg. KDensity - Scientific Machine Learning (Core)	28.27
Avg. KDensity - Supporting Papers	3.47
Citations with Highlights in PDF	332
PDF Highlights Coverage	64.1%
Citations with Keyword Matches	508
Keyword Match Coverage	98.1%

Table 4: Journal and Publisher Distribution

Publisher/Source	N	Percentage
arXiv Preprint	182	35.1%
Elsevier	101	19.5%
Other Publishers	76	14.7%
Springer	27	5.2%
Nature Publishing	20	3.9%
Conference Proceedings	15	2.9%
IEEE	14	2.7%
Science/AAAS	14	2.7%
SIAM	12	2.3%
PNAS	11	2.1%
Not Specified	9	1.7%
Wiley	8	1.5%
APS (Physical Review)	7	1.4%
AIP Publishing	6	1.2%
ACM	5	1%

Table 5: Document Type Distribution

Document Type	N	Percentage
Paper	462	89.2%
Book	20	3.9%
Software	9	1.7%
Slides	6	1.2%
Chapter	5	1%
PhDThesis	4	0.8%
TechReport	4	0.8%
Video	3	0.6%
BScThesis	2	0.4%
Article	1	0.2%
MastersThesis	1	0.2%
Patent	1	0.2%

Citation Format Specification

Standard Format: Author(s), Year. *Title*. Journal/Publisher, Volume(Issue): Pages. DOI: [identifier]. KDensity: [score]. Repository: [URL]. References: [count].

Metadata Fields:

- **K-Density Score:** Kernel density estimation score for citation impact
- **Repository Link:** GitHub or institutional repository URL when available
- **Reference Count:** Number of references cited within the document

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1. Physics-Informed Learning Machines, SciML, PINNs

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Processing Summary

Files generated:

- `citations.bib` - BibTeX bibliography file
- `citations_dataframe.csv` - Structured dataset for analysis
- `piml-citations-455.html` - HTML web report
- `piml-citations-455.pdf` - PDF report

Vault citations folder statistics:

- Referenced folder: 462 citations
- Supporting folder: 56 citations
- Unreferenced folder: 0 citations
- Scientific Machine Learning (Core): 462 citations
- Supporting Papers: 56 citations
- No Rated Papers: 0 citations