Physics-Informed Learning Machines Literature

536 Citations from my *Physics of Data* Obsidian vault

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Citation Bibliography - PhysicsOfData Vault

Executive Summary

Total Citations Found: 536

Table 1: Citation Categorization Summary

Category	Number of Citations	Percentage
Scientific Machine Learning (Core)	482	89.9%
Supporting Papers	54	10.1%

Bibliometric Analysis

Table 2: Temporal and Repository Coverage

Metric	Value
Publication Year Range	1915 - 2025
Median Publication Year	2019
Most Productive Decade	2020s (262 citations)
Citations with Git Repositories	159
Repository Coverage Rate	29.7%
Citations with Reference Counts	512
Reference Data Coverage	95.5%
Average References per Citation	60.7
Citations with KDensity Scores	536
KDensity Coverage Rate	100%

Table 3: Quality and Impact Metrics

Metric	Value
Avg. KDensity - Scientific Machine Learning (Core)	27.75
Avg. KDensity - Supporting Papers	3.35
Citations with Highlights in PDF	358
PDF Highlights Coverage	66.8%
Citations with Keyword Matches	526
Keyword Match Coverage	98.1%

Table 4: Journal and Publisher Distribution

Publisher/Source	N	Percentage
arXiv Preprint	185	34.5%
Elsevier	110	20.5%
Other Publishers	76	14.2%
Springer	27	5%
Nature Publishing	20	3.7%
IEEE	16	3%
Conference Proceedings	15	2.8%
SIAM	14	2.6%
Science/AAAS	14	2.6%
PNAS	11	2.1%
Not Specified	10	1.9%
Wiley	8	1.5%
APS (Physical Review)	7	1.3%
AIP Publishing	6	1.1%
ACM	5	0.9%

Table 5: Document Type Distribution

Document Type	N	Percentage
Paper	479	89.4%
Book	20	3.7%
Software	9	1.7%
Slides	7	1.3%
Chapter	5	0.9%
PhDThesis	4	0.7%
TechReport	4	0.7%
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-sciml-citations.html` - HTML web report
- `piml-sciml-citations.pdf` - PDF report

Vault citations folder statistics:

- Referenced folder: 482 citations
- Supporting folder: 54 citations
- Unreferenced folder: 0 citations
- Scientific Machine Learning (Core): 482 citations
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