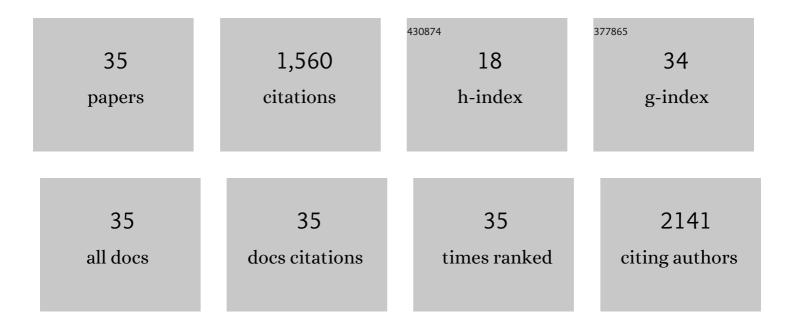
Jason R Hattrick-Simpers

List of Publications by Year in descending order

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#	Article	IF	CITATIONS
1	Accelerated discovery of metallic glasses through iteration of machine learning and high-throughput experiments. Science Advances, 2018, 4, eaaq1566.	10.3	354
2	Applications of high throughput (combinatorial) methodologies to electronic, magnetic, optical, and energy-related materials. Journal of Applied Physics, 2013, 113, .	2.5	202
3	On-the-fly closed-loop materials discovery via Bayesian active learning. Nature Communications, 2020, 11, 5966.	12.8	167
4	Can machine learning identify the next high-temperature superconductor? Examining extrapolation performance for materials discovery. Molecular Systems Design and Engineering, 2018, 3, 819-825.	3.4	149
5	Materials science in the artificial intelligence age: high-throughput library generation, machine learning, and a pathway from correlations to the underpinning physics. MRS Communications, 2019, 9, 821-838.	1.8	109
6	Perspective: Composition–structure–property mapping in high-throughput experiments: Turning data into knowledge. APL Materials, 2016, 4, .	5.1	87
7	Combinatorial investigation of magnetostriction in Fe–Ga and Fe–Ga–Al. Applied Physics Letters, 2008, 93, .	3.3	38
8	A simple constrained machine learning model for predicting high-pressure-hydrogen-compressor materials. Molecular Systems Design and Engineering, 2018, 3, 509-517.	3.4	37
9	Generalized machine learning technique for automatic phase attribution in time variant high-throughput experimental studies. Journal of Materials Research, 2015, 30, 879-889.	2.6	35
10	The Materials Super Highway: Integrating High-Throughput Experimentation into Mapping the Catalysis Materials Genome. Catalysis Letters, 2015, 145, 290-298.	2.6	31
11	A High-Throughput Structural and Electrochemical Study of Metallic Glass Formation in Ni–Ti–Al. ACS Combinatorial Science, 2020, 22, 330-338.	3.8	31
12	A high-throughput investigation of Fe–Cr–Al as a novel high-temperature coating for nuclear cladding materials. Nanotechnology, 2015, 26, 274003.	2.6	28
13	Semi-Supervised Approach to Phase Identification from Combinatorial Sample Diffraction Patterns. Jom, 2016, 68, 2116-2125.	1.9	27
14	Combinatorial Investigation of Ferromagnetic Shape-Memory Alloys in the Ni-Mn-Al Ternary System Using a Composition Spread Technique. Materials Transactions, 2004, 45, 173-177.	1.2	26
15	The Different Roles of Entropy and Solubility in High Entropy Alloy Stability. ACS Combinatorial Science, 2016, 18, 596-603.	3.8	26
16	Combinatorial Approach to Turbine Bond Coat Discovery. ACS Combinatorial Science, 2013, 15, 419-424.	3.8	22
17	Raman spectroscopic observation of dehydrogenation in ball-milled LiNH2–LiBH4–MgH2 nanoparticles. International Journal of Hydrogen Energy, 2010, 35, 6323-6331.	7.1	21
18	High-throughput screening of shape memory alloy thin-film spreads using nanoindentation. Journal of Applied Physics, 2008, 104, .	2.5	19

#	Article	IF	CITATIONS
19	Self-healing catalysts: Co ₃ O ₄ nanorods for Fischer–Tropsch synthesis. Chemical Communications, 2014, 50, 4575-4578.	4.1	16
20	Automated Phase Segmentation for Large-Scale X-ray Diffraction Data Using a Graph-Based Phase Segmentation (GPhase) Algorithm. ACS Combinatorial Science, 2017, 19, 137-144.	3.8	16
21	High-throughput screening of magnetic properties of quenched metallic-alloy thin-film composition spreads. Applied Surface Science, 2007, 254, 734-737.	6.1	15
22	Integrated Highâ€Throughput and Machine Learning Methods to Accelerate Discovery of Molten Salt Corrosionâ€Resistant Alloys. Advanced Science, 2022, 9, e2200370.	11.2	15
23	Demonstration of magnetoelectric scanning probe microscopy. Review of Scientific Instruments, 2007, 78, 106103.	1.3	12
24	Discovering exceptionally hard and wear-resistant metallic glasses by combining machine-learning with high throughput experimentation. Applied Physics Reviews, 2022, 9, .	11.3	12
25	An Inter-Laboratory Study of Zn–Sn–Ti–O Thin Films using High-Throughput Experimental Methods. ACS Combinatorial Science, 2019, 21, 350-361.	3.8	11
26	Aggressively optimizing validation statistics can degrade interpretability of data-driven materials models. Journal of Chemical Physics, 2021, 155, 054105.	3.0	10
27	Data Analysis in Combinatorial Experiments: Applying Supervised Principal Component Technique to Investigate the Relationship Between ToF-SIMS Spectra and the Composition Distribution of Ternary Metallic Alloy Thin Films. QSAR and Combinatorial Science, 2008, 27, 171-178.	1.4	7
28	Development of a High - Throughput Methodology for Screening Coking Resistance of Modified Thin - Film Catalysts. ACS Combinatorial Science, 2012, 14, 372-377.	3.8	7
29	Towards Automated Design of Corrosion Resistant Alloy Coatings with an Autonomous Scanning Droplet Cell. Jom, 2022, 74, 2941-2950.	1.9	7
30	NGenE 2021: Electrochemistry Is Everywhere. ACS Energy Letters, 2022, 7, 368-374.	17.4	6
31	Optical cell for combinatorialin situRaman spectroscopic measurements of hydrogen storage materials at high pressures and temperatures. Review of Scientific Instruments, 2011, 82, 033103.	1.3	5
32	Experimental assessment of thin film high pressure metal hydride material properties. International Journal of Hydrogen Energy, 2018, 43, 18363-18371.	7.1	5
33	An Open Combinatorial Diffraction Dataset Including Consensus Human and Machine Learning Labels with Quantified Uncertainty for Training New Machine Learning Models. Integrating Materials and Manufacturing Innovation, 2021, 10, 311-318.	2.6	5
34	A combinatorial characterization scheme for high-throughput investigations of hydrogen storage materials. Science and Technology of Advanced Materials, 2011, 12, 054207.	6.1	1
35	Comment on "A simple constrained machine learning model for predicting high-pressure-hydrogen-compressor materials―by Hattrick-Simpers, <i>et al.</i> , <i>Molecular Systems Design & Engineering</i> , 2018, 3 , 509. Molecular Systems Design and Engineering, 2020, 5, 589-591.	3.4	1