

Johan A Westerhuis

List of Publications by Year in descending order

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Version: 2024-02-01

77
papers

7,323
citations

218381

26
h-index

66788

78
g-index

80
all docs

80
docs citations

80
times ranked

10712
citing authors

#	ARTICLE	IF	CITATIONS
1	Effect of strigolactones on recruitment of the rice root-associated microbiome. <i>FEMS Microbiology Ecology</i> , 2022, 98, .	1.3	29
2	Elevation of fatty acid desaturase ^{Δ2} in esophageal adenocarcinoma increases polyunsaturated lipids and may exacerbate bile acid-induced DNA damage. <i>Clinical and Translational Medicine</i> , 2022, 12, e810.	1.7	6
3	A beginner's guide to integrating multi-omics data from microbial communities. <i>Biochemist</i> , 2022, 44, 23-29.	0.2	5
4	Heterofusion: Fusing genomics data of different measurement scales. <i>Journal of Chemometrics</i> , 2021, 35, e3200.	0.7	5
5	<i><i>Divide et impera</i></i> : How disentangling common and distinctive variability in multiset data analysis can aid industrial process troubleshooting and understanding. <i>Journal of Chemometrics</i> , 2021, 35, e3266.	0.7	4
6	Generalized simultaneous component analysis of binary and quantitative data. <i>Journal of Chemometrics</i> , 2021, 35, e3312.	0.7	3
7	Systematic selection of competing metabolomics methods in a metabolite-sensory relationship study. <i>Metabolomics</i> , 2021, 17, 77.	1.4	3
8	Integration of omics data to unravel root microbiome recruitment. <i>Current Opinion in Biotechnology</i> , 2021, 70, 255-261.	3.3	20
9	Repeated measures ASCA+ for analysis of longitudinal intervention studies with multivariate outcome data. <i>PLoS Computational Biology</i> , 2021, 17, e1009585.	1.5	21
10	Targeted proteomic response to coffee consumption. <i>European Journal of Nutrition</i> , 2020, 59, 1529-1539.	1.8	2
11	Common and distinct variation in data fusion of designed experimental data. <i>Metabolomics</i> , 2020, 16, 2.	1.4	13
12	Separating common (global and local) and distinct variation in multiple mixed types data sets. <i>Journal of Chemometrics</i> , 2020, 34, e3197.	0.7	7
13	Increased comparability between RNA-Seq and microarray data by utilization of gene sets. <i>PLoS Computational Biology</i> , 2020, 16, e1008295.	1.5	18
14	Logistic principal component analysis via non-convex singular value thresholding. <i>Chemometrics and Intelligent Laboratory Systems</i> , 2020, 204, 104089.	1.8	9
15	Harmonization of quality metrics and power calculation in multi-omic studies. <i>Nature Communications</i> , 2020, 11, 3092.	5.8	43
16	Variable selection and validation in multivariate modelling. <i>Bioinformatics</i> , 2019, 35, 972-980.	1.8	122
17	Weighted sparse principal component analysis. <i>Chemometrics and Intelligent Laboratory Systems</i> , 2019, 195, 103875.	1.8	10
18	STATegra, a comprehensive multi-omics dataset of B-cell differentiation in mouse. <i>Scientific Data</i> , 2019, 6, 256.	2.4	26

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19	Principal component analysis of binary genomics data. <i>Briefings in Bioinformatics</i> , 2019, 20, 317-329.	3.2	21
20	GC-MS-based urinary organic acid profiling reveals multiple dysregulated metabolic pathways following experimental acute alcohol consumption. <i>Scientific Reports</i> , 2018, 8, 5775.	1.6	17
21	iTOP: inferring the topology of omics data. <i>Bioinformatics</i> , 2018, 34, i988-i996.	1.8	19
22	Lipidomic Response to Coffee Consumption. <i>Nutrients</i> , 2018, 10, 1851.	1.7	32
23	Fusing metabolomics data sets with heterogeneous measurement errors. <i>PLoS ONE</i> , 2018, 13, e0195939.	1.1	7
24	Training for translation between disciplines: a philosophy for life and data sciences curricula. <i>Bioinformatics</i> , 2018, 34, i4-i12.	1.8	5
25	The ¹ H-NMR-based metabolite profile of acute alcohol consumption: A metabolomics intervention study. <i>PLoS ONE</i> , 2018, 13, e0196850.	1.1	18
26	Metabolomics variable selection and classification in the presence of observations below the detection limit using an extension of ERp. <i>BMC Bioinformatics</i> , 2017, 18, 83.	1.2	6
27	Selecting the number of factors in principal component analysis by permutation testing—Numerical and practical aspects. <i>Journal of Chemometrics</i> , 2017, 31, e2937.	0.7	22
28	Why orthogonal rotations might be not so orthogonal as you think. <i>Journal of Chemometrics</i> , 2017, 31, e2920.	0.7	1
29	Separating common from distinctive variation. <i>BMC Bioinformatics</i> , 2016, 17, 195.	1.2	18
30	Variable selection for binary classification using error rate p-values applied to metabolomics data. <i>BMC Bioinformatics</i> , 2016, 17, 33.	1.2	5
31	Gut microbial activity as influenced by fiber digestion: dynamic metabolomics in an in vitro colon simulator. <i>Metabolomics</i> , 2016, 12, 1.	1.4	17
32	Contribution towards a Metabolite Profile of the Detoxification of Benzoic Acid through Glycine Conjugation: An Intervention Study. <i>PLoS ONE</i> , 2016, 11, e0167309.	1.1	23
33	Using Petri nets for experimental design in a multi-organ elimination pathway. <i>Computers in Biology and Medicine</i> , 2015, 63, 19-27.	3.9	1
34	Analyzing metabolomics-based challenge tests. <i>Metabolomics</i> , 2015, 11, 50-63.	1.4	17
35	Network Identification of Hormonal Regulation. <i>PLoS ONE</i> , 2014, 9, e96284.	1.1	5
36	Reflections on univariate and multivariate analysis of metabolomics data. <i>Metabolomics</i> , 2014, 10, 361-374.	1.4	406

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37	Variable importance in latent variable regression models. <i>Journal of Chemometrics</i> , 2014, 28, 615-622.	0.7	42
38	Population-based nutrkinetic modeling of polyphenol exposure. <i>Metabolomics</i> , 2014, 10, 1059-1073.	1.4	20
39	Identifying inhibitory compounds in lignocellulosic biomass hydrolysates using an exometabolomics approach. <i>BMC Biotechnology</i> , 2014, 14, 22.	1.7	55
40	Use of prior knowledge for the analysis of high-throughput transcriptomics and metabolomics data. <i>BMC Systems Biology</i> , 2014, 8, S2.	3.0	23
41	A technical note on challenge tests in human volunteers for multidimensional phenotyping. <i>Chemometrics and Intelligent Laboratory Systems</i> , 2014, 136, 81-84.	1.8	2
42	Application of NMR-based metabonomics suggests a relationship between betaine absorption and elevated creatine plasma concentrations in catheterised sows. <i>British Journal of Nutrition</i> , 2012, 107, 1603-1615.	1.2	15
43	Topology of Transcriptional Regulatory Networks: Testing and Improving. <i>PLoS ONE</i> , 2012, 7, e40082.	1.1	1
44	Double-check: validation of diagnostic statistics for PLS-DA models in metabolomics studies. <i>Metabolomics</i> , 2012, 8, 3-16.	1.4	622
45	Editorial "data analysis in metabolomics. <i>Metabolomics</i> , 2012, 8, 1-2.	1.4	2
46	Metabolic fate of polyphenols in the human superorganism. <i>Proceedings of the National Academy of Sciences of the United States of America</i> , 2011, 108, 4531-4538.	3.3	448
47	New Figures of Merit for Comprehensive Functional Genomics Data: The Metabolomics Case. <i>Analytical Chemistry</i> , 2011, 83, 3267-3274.	3.2	22
48	Simplivariate Models: Uncovering the Underlying Biology in Functional Genomics Data. <i>PLoS ONE</i> , 2011, 6, e20747.	1.1	13
49	Data-processing strategies for metabolomics studies. <i>TrAC - Trends in Analytical Chemistry</i> , 2011, 30, 1685-1698.	5.8	164
50	ANOVA "principal component analysis and ANOVA "simultaneous component analysis: a comparison. <i>Journal of Chemometrics</i> , 2011, 25, 561-567.	0.7	119
51	Tracy "Widom statistic for the largest eigenvalue of autoscaled real matrices. <i>Journal of Chemometrics</i> , 2011, 25, 644-652.	0.7	17
52	Multivariate paired data analysis: multilevel PLS-DA versus OPLS-DA. <i>Metabolomics</i> , 2010, 6, 119-128.	1.4	362
53	Multiway analysis of flux distributions across multiple conditions. <i>Journal of Chemometrics</i> , 2009, 23, 406-420.	0.7	23
54	Metabolomics data exploration guided by prior knowledge. <i>Analytica Chimica Acta</i> , 2009, 651, 173-181.	2.6	28

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55	Exploring the analysis of structured metabolomics data. <i>Chemometrics and Intelligent Laboratory Systems</i> , 2009, 98, 88-96.	1.8	27
56	Phenotyping Tea Consumers by Nutrikinetic Analysis of Polyphenolic End-Metabolites. <i>Journal of Proteome Research</i> , 2009, 8, 3317-3330.	1.8	89
57	Assessment of PLSDA cross validation. <i>Metabolomics</i> , 2008, 4, 81-89.	1.4	1,178
58	Discriminant Q2 (DQ2) for improved discrimination in PLSDA models. <i>Metabolomics</i> , 2008, 4, 293-296.	1.4	69
59	PARAFASCA: ASCA combined with PARAFAC for the analysis of metabolic fingerprinting data. <i>Journal of Chemometrics</i> , 2008, 22, 114-121.	0.7	52
60	The geometry of ASCA. <i>Journal of Chemometrics</i> , 2008, 22, 464-471.	0.7	19
61	Multilevel Data Analysis of a Crossover Designed Human Nutritional Intervention Study. <i>Journal of Proteome Research</i> , 2008, 7, 4483-4491.	1.8	158
62	Simplivariate Models: Ideas and First Examples. <i>PLoS ONE</i> , 2008, 3, e3259.	1.1	16
63	Grey component analysis. <i>Journal of Chemometrics</i> , 2007, 21, 474-485.	0.7	19
64	Statistical validation of megavariable effects in ASCA. <i>BMC Bioinformatics</i> , 2007, 8, 322.	1.2	137
65	Performance assessment and improvement of control charts for statistical batch process monitoring. <i>Statistica Neerlandica</i> , 2006, 60, 339-360.	0.9	14
66	Centering, scaling, and transformations: improving the biological information content of metabolomics data. <i>BMC Genomics</i> , 2006, 7, 142.	1.2	1,836
67	Maximum likelihood scaling (MALS). <i>Journal of Chemometrics</i> , 2006, 20, 120-127.	0.7	9
68	ASCA: analysis of multivariate data obtained from an experimental design. <i>Journal of Chemometrics</i> , 2005, 19, 469-481.	0.7	201
69	Model Selection and Optimal Sampling in High-Throughput Experimentation. <i>Analytical Chemistry</i> , 2004, 76, 3171-3178.	3.2	14
70	A framework for sequential multiblock component methods. <i>Journal of Chemometrics</i> , 2003, 17, 323-337.	0.7	190
71	Near-Infrared Spectroscopic Monitoring of a Series of Industrial Batch Processes Using a Bilinear Grey Model. <i>Applied Spectroscopy</i> , 2003, 57, 1007-1019.	1.2	18
72	Kinetic and mechanistic studies on the Heck reaction using real-time near infrared spectroscopy. <i>Physical Chemistry Chemical Physics</i> , 2003, 5, 4455-4460.	1.3	12

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73	Monitoring of batch processes using spectroscopy. AICHE Journal, 2002, 48, 2283-2297.	1.8	53
74	Deflation in multiblock PLS. Journal of Chemometrics, 2001, 15, 485-493.	0.7	81
75	Modelling of spectroscopic batch process data using grey models to incorporate external information. Journal of Chemometrics, 2001, 15, 101-121.	0.7	38
76	Multiway multiblock component and covariates regression models. Journal of Chemometrics, 2000, 14, 301-331.	0.7	92
77	StandardizedQ-statistic for improved sensitivity in the monitoring of residuals in MSPC. Journal of Chemometrics, 2000, 14, 335-349.	0.7	34