Science desperately needs disruptive innovation

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Abstract

Disruption – the holy grail of the hi-tech industry – is actively sought by academic institutes, research funds and governments wishing to promote science and monetize its fruits. Nonetheless, there is no methodological framework for disrupting science. Studies seeking this framework focus on Scientific conduct without integrating the vast hi-tech disruption methodologies and experience. To cross this barrier, we developed a new Disruption Index (DI), enabling cross-analyses between hi-tech and science for the first time. The two fields show similar disruption patterns. However, data show that while hi-tech quickly identifies and harnesses innovation advancements, science lags in both and is highly affected by exogenous shifts. Decision-makers can leverage the framework suggested here to assimilate the hi-tech disruption mindset in science.

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1. Introduction

Incremental Progression (InP) is the fundamental scientific methodology pushing humanity forward from one discovery to the next. It guides the perception of scientists of all levels and disciplines to evolve step by step, ensures continuous activity and gradual progress. This systematic mechanism is highly effective within a defined context, or paradigm, when low-hanging fruits are discovered one after the other. Its effectiveness placed the InP in the scientific comfort zone. However, InP also tunnels scientists to delve into niches where they become experts while narrowing their scope of thinking. Higher-hanging fruits, such as complex phenomena exceeding one's specialty (e.g., climate change multi-effect), became more challenging to study and explain. As a result, some scientific disciplines reached stagnation and scientific research is much less effective (Collison and Nielsen, 2018; Park et al., 2023).

The hi-tech world, especially technological startups and venture-capital funds, understands the high alternative cost of such stagnation – loss occurring by not trying other, less obvious, directions. They, therefore, proactively pursue innovation that will shake existing knowledge and create new realities. This pursuit is expressed by investing in paths that will hopefully lead to **Disruptions** (i.e., breakthroughs), jumpstarting the entire market, and initiating a swarm of consecutive investments. Notable examples of technological disruptions are the Internet, smartphones, and most recently Generative AI, which affect various aspects of our lives.

Many governments and funding agencies acknowledged scientific stagnation as a strategic threat to economic growth. They invest in scientific research, despite its plummeting effectiveness (Bloom et al., 2020). These bodies understand the importance of disruptive factors, and thus seek ways to increase innovation (Ip) and invest in high-risk, high-gain projects (e.g., the European Research Council funding schemes, https://erc.europa.eu/). The investments highlight directions believed to produce breakthroughs, or in other words, disrupt science. However, breakthroughs are only proven (or not) in hindsight since disruptive thinking is yet to be structured and understood.

Our research hypothesis claims that while InP is ingrained in the modus operandi of most scientific and industrial paradigms, disruptive thinking, which jumpstarts these fields from one phase to another, remains untaught, serendipitous, and yet highly desirable. Previous studies aiming to define the dynamics of scientific breakthroughs analyzed the effect of research team sizes, the numbers and impact of citations and patents, the depletion of low-hanging fruit and the de-focus of scientific incentives, among other directions (Collison and Nielsen, 2018; Wu et al., 2019; Bhattacharya and Packalen, 2020; Bloom et al., 2020; Bhaskar, 2021; Bornmann et al., 2020a; Bornmann et al., 2020b; Min et al., 2021; Xu et al., 2022; Park et al., 2023; Shepherd, 2023). Since these studies focus on scientific conduct, they do not enable a comparison between hi-tech and science. To cross this barrier, we define a new **Disruption Index** (DI) and apply it to both fields, while analyzing similarity in disruption patterns (see next section for explanations). The new index and terminology will make disruptive thinking part of the scientific toolbox rather than a serendipitous surprise, thereby helping to accelerate the progress of both science and hi-tech.

2. Data and methods

2.1. Data sources

The **hi-tech** dataset was extracted from Crunchbase Data (data.crunchbase.com; Table 1). It refers to all types of funding rounds of hi-tech companies between 1991-2020 in: Cloud Storage, Mobile Apps, Quantum Computing, Artificial Intelligence, Big Data, Virtual Reality, Blockchain, Cryptocurrency, E-Learning, 3D Printing, Internet Of Things, SEO, Social Media, InsurTech, and Mobile Advertising. The **remote-science** dataset was derived from the Web of Science online databases (webofscience.com; Table 2). It includes the top 10,000 cited papers between 1984-2020 in Geosciences, Economics, Psychology, Mathematics, and Statistics. The **tech-science** dataset was derived from Google Scholar (scholar.google.com; Table 3). It represents the yearly number of peer-reviewed papers published between 1991-2020 in the Quantum Computing and Artificial Intelligence research disciplines. Given their relatively young age, these disciplines cannot be examined according to the number of citations for each paper, as we do with **remote-science**.

Table 1. Hi-tech dataset and calculations: $M – investments in millions of dollars, NI – BP as Number of Investments, DI – Disruption Index, DP – Disruption Pattern.

(a)	*Cloud Storage*				*Mobile Apps*				*Quantum computing*			
Year	**$M**	**NI**	**DI**	**DP**	**$M**	**NI**	**DI**	**DP**	**$M**	**NI**	**DI**	**DP**
1991	0	0	0	0	0	0	0	0	0	0	0	0
1992	0	0	0	0	0	0	0	0	0	0	0	0
1993	0	0	0	0	NA	1	0.01	0	0	0	0	0
1994	0	0	0	0	0	0	0	0	0	0	0	0
1995	0	0	0	0	0	0	0	0	0	0	0	0
1996	0	0	0	0	10	1	0.01	0	0	0	0	0
1997	0	0	0	0	NA	2	0.02	0	0	0	0	0
1998	0	0	0	0	0.1	1	0.01	0	0	0	0	0
1999	11.8	1	0.25	0.23	38.1	4	0.04	0	0	0	0	0
2000	63.1	8	1.98	0.46	220.6	19	0.20	0.12	0	0	0	0
2001	45.4	3	0.74	0.68	135.1	13	0.14	0.25	0	0	0	0
2002	18	3	0.74	0.91	117.4	16	0.17	0.37	NA	2	1.00	0.21
2003	21.9	4	0.99	1.14	83.8	14	0.15	0.50	0	0	0	0.41
2004	33.8	5	1.23	1.37	168.3	20	0.21	0.62	0.025	1	0.50	0.62
2005	33.5	2	0.49	1.60	191.8	36	0.38	0.75	0	0	0	0.83
2006	37.5	6	1.48	1.82	266.7	35	0.37	0.87	14	1	0.50	1.04
2007	20	1	0.25	2.05	241.9	48	0.50	1.00	0	0	0	1.24
2008	88.3	15	3.70	2.28	349.3	65	0.68	1.12	18	2	1.00	1.45
2009	58.9	10	2.47	2.51	244.1	96	1.00	1.25	0.9	1	0.50	1.66
2010	95.3	11	2.72	2.74	343.2	135	1.41	1.37	2.3	2	1.00	1.87
2011	167.6	12	2.96	2.96	1289	241	2.52	3.29	20	2	1.00	2.07

2012	153	21	5.19	5.09	819.5	332	3.47	5.21	31.2	2	1.00	2.28
2013	123	25	6.17	7.21	2008.4	482	5.05	7.13	29.8	5	2.49	2.49
2014	122.4	32	7.90	9.33	7782.7	766	8.02	9.05	112.4	17	8.46	8.46
2015	160.5	33	8.15	11.46	14138.6	1063	11.13	10.97	64.2	15	7.46	7.46
2016	513.5	55	13.58	13.58	15185.3	1235	12.93	12.88	79.2	8	3.98	3.98
2017	440.9	56	13.83	13.83	18426.9	1234	12.92	13.19	247.7	20	9.95	9.83
2018	401.3	39	9.63	10.25	12639	1294	13.54	13.50	149.4	33	16.42	15.67
2019	143	27	6.67	6.67	12861.3	1234	12.92	12.84	179.5	35	17.41	21.52
2020	593.9	36	8.89	8.89	11555.2	1167	12.21	12.17	534.7	55	27.36	27.36
(b)	**Artificial Intelligence**				**Big Data**				**Virtual Reality**			
Year	**$M**	**NI**	**DI**	**DP**	**$M**	**NI**	**DI**	**DP**	**$M**	**NI**	**DI**	**DP**
1991	0	0	0	0	0	0	0	0	0	0	0	0
1992	0	0	0	0	0	0	0	0	0	0	0	0
1993	NA	1	0.00	0	0	0	0	0	0	0	0	0
1994	0	0	0	0	0	0	0	0	0	0	0	0
1995	NA	1	0.00	0	0	0	0	0	0	0	0	0
1996	7.8	3	0.01	0	0.4	2	0.02	0	0	0	0	0
1997	8.1	3	0.01	0	0	0	0	0	0.4	1	0.04	0.13
1998	20.7	6	0.03	0	1.9	1	0.01	0	1.68	1	0.04	0.27
1999	49.5	7	0.03	0	85.2	8	0.08	0.11	0.38	3	0.11	0.40
2000	312.4	33	0.14	0.09	206.4	15	0.15	0.21	26.46	5	0.18	0.53
2001	191.6	24	0.10	0.18	92.3	9	0.09	0.32	84.05	7	0.25	0.67
2002	101.2	18	0.08	0.27	163.4	17	0.17	0.42	51.08	3	0.11	0.80
2003	123.1	28	0.12	0.37	76	14	0.14	0.53	9.86	4	0.14	0.93
2004	169.5	29	0.12	0.46	131.7	24	0.24	0.63	28.30	11	0.39	1.07
2005	168.8	35	0.15	0.55	303.5	44	0.44	0.74	61.04	10	0.35	1.20
2006	284.8	43	0.18	0.64	403.9	60	0.60	0.84	74.99	10	0.35	1.33
2007	446.7	66	0.28	0.73	597.7	62	0.62	0.95	372.44	12	0.42	1.47
2008	386.3	97	0.41	0.82	479.7	106	1.06	1.05	113.76	20	0.71	1.60
2009	325	104	0.44	0.92	457	172	1.72	2.64	286.99	13	0.46	1.73
2010	560	174	0.74	1.01	784.3	289	2.90	4.23	115.88	22	0.78	1.87
2011	911.4	267	1.13	1.10	1315.7	240	2.40	5.82	1634.69	31	1.10	2.00
2012	1412	486	2.05	3.39	1441.6	469	4.70	7.41	83.61	49	1.73	2.13
2013	2546	820	3.46	5.68	3288.3	705	7.06	9.00	244.26	64	2.27	2.27
2014	5966	1242	5.25	7.98	4641.3	1011	10.13	10.59	297.582	160	5.66	9.79
2015	9201	1859	7.85	10.27	6079.7	1217	12.19	12.18	721.076	275	9.73	17.32
2016	16295	2639	11.15	12.56	4878.1	1176	11.78	12.02	4208.5	702	24.85	24.85
2017	26497	3460	14.62	14.86	6605.6	1220	12.22	11.86	1509.9	435	15.40	20.96
2018	30021	4066	17.18	17.15	7647.3	1168	11.70	11.69	1238.6	399	14.12	17.08
2019	33304	4149	17.53	17.03	8063.9	1024	10.26	10.49	1434.7	325	11.50	13.19

2020	31245	4008	16.93	16.90	9514.4	927	9.29	9.28	1072.7	263	9.31	9.31
(c)	**Blockchain**				**Cryptocurrency**				**E-Learning**			
Year	**$M**	**NI**	**DI**	**DP**	**$M**	**NI**	**DI**	**DP**	**$M**	**NI**	**DI**	**DP**
1991	0	0	0	0	0	0	0	0	0	0	0	0
1992	0	0	0	0	0	0	0	0	0	0	0	0
1993	0	0	0	0	0	0	0	0	0	0	0	0
1994	0	0	0	0	0	0	0	0	0	0	0	0
1995	0	0	0	0	0	0	0	0	0	0	0	0
1996	0	0	0	0	0	0	0	0	0	0	0	0
1997	0	0	0	0	0	0	0	0	0	0	0	0
1998	0	0	0	0	0	0	0	0	3.2	2	0.06	0.10
1999	2.4	1	0.02	0.03	0	0	0	0	78.2	4	0.11	0.19
2000	0	1	0.02	0.05	0	0	0	0	340.7	17	0.47	0.29
2001	0	0	0	0.08	0	0	0	0	103	12	0.33	0.38
2002	0	0	0	0.11	0	0	0	0	31.8	7	0.19	0.48
2003	8	2	0.05	0.14	0	0	0	0	28.5	2	0.06	0.57
2004	0	1	0.02	0.16	0	0	0	0	184.2	7	0.19	0.67
2005	10	1	0.02	0.19	5.6	1	0.04	0.05	9.5	5	0.14	0.76
2006	10	2	0.05	0.22	0	1	0.04	0.11	30.3	12	0.33	0.86
2007	29	2	0.05	0.24	0	1	0.04	0.16	245.3	21	0.58	0.96
2008	0	0	0	0.27	0	0	0	0.22	122	24	0.66	1.05
2009	10.5	5	0.12	0.30	3.9	5	0.22	0.27	85.8	31	0.86	1.15
2010	41.9	6	0.14	0.33	23.3	4	0.17	0.32	177.7	45	1.24	1.24
2011	46	15	0.36	0.35	67.6	6	0.26	0.38	80.1	63	1.74	3.01
2012	53.7	16	0.38	0.38	6.7	10	0.43	0.43	419.7	147	4.06	4.78
2013	108	47	1.12	1.92	116.3	37	1.59	2.41	504.738	195	5.39	6.55
2014	645.6	146	3.47	3.47	271.2	102	4.39	4.39	1014.7	269	7.43	8.31
2015	357.2	156	3.70	3.70	469.3	109	4.69	4.87	1851.3	378	10.44	10.08
2016	597.3	275	6.53	7.08	516.4	124	5.34	5.34	2091.7	429	11.85	11.85
2017	1293	546	12.97	10.46	997	284	12.23	9.83	1665.8	431	11.91	12.93
2018	3472	1165	27.67	13.84	3215.7	595	25.62	14.32	4346.5	507	14.01	14.01
2019	2901	957	22.73	17.21	2341.9	502	21.62	18.81	2819.8	480	13.26	14.35
2020	2295	867	20.59	20.59	3959.4	541	23.30	23.30	10521.5	532	14.70	14.70
(d)	**3D Printing**				**Internet of Things**				**SEO**			
Year	**$M**	**NI**	**DI**	**DP**	**$M**	**NI**	**DI**	**DP**	**$M**	**NI**	**DI**	**DP**
1991	0	0	0	0	0	0	0	0	0	0	0	0
1992	0	0	0	0	0	0	0	0	0	0	0	0

1993	0	0	0	0	0	0	0	0	0	0	0	0
1994	0	0	0	0	0	0	0	0	0	0	0	0
1995	0	0	0	0	0.6	2	0.03	0.09	0	0	0	0
1996	0	0	0	0	17.3	5	0.07	0.18	0	0	0	0
1997	0	0	0	0	22.6	5	0.07	0.26	0	0	0	0
1998	0	0	0	0	18.3	2	0.03	0.35	0	0	0	0
1999	0	0	0	0	82.4	15	0.20	0.44	0.02	1	0.16	0.13
2000	0	0	0	0	479.3	39	0.53	0.53	40	4	0.65	0.27
2001	0	0	0	0	175.2	15	0.20	0.61	2.5	2	0.32	0.40
2002	0	0	0	0	80.2	13	0.18	0.70	0.3	2	0.32	0.54
2003	8.8	2	0.19	0.08	80.7	9	0.12	0.79	2.25	2	0.32	0.67
2004	4.3	2	0.19	0.16	82.5	12	0.16	0.88	19.75	5	0.81	0.81
2005	29.9	6	0.56	0.25	306.7	23	0.31	0.97	32.14	13	2.10	1.98
2006	21.5	4	0.37	0.33	149.2	19	0.26	1.05	55.10	17	2.75	3.15
2007	44.4	7	0.65	0.41	363.8	40	0.54	1.14	252.74	23	3.72	4.31
2008	4.4	4	0.37	0.49	254	42	0.57	1.23	114.01	22	3.56	5.48
2009	12.1	4	0.37	0.58	201.3	49	0.66	1.32	45.97	24	3.88	6.65
2010	15.7	9	0.83	0.66	272.8	86	1.17	1.40	51.13	49	7.93	7.82
2011	9.3	8	0.74	0.74	333.6	110	1.49	1.49	61.11	41	6.63	8.99
2012	33.7	25	2.32	4.20	626.6	179	2.43	3.96	159.59	55	8.90	10.16
2013	123.6	63	5.84	7.65	767.5	331	4.49	6.43	183.88	70	11.33	11.33
2014	130.2	128	11.87	11.11	1505	602	8.17	8.89	73.23	57	9.22	9.59
2015	405.8	157	14.56	14.56	1978.3	875	11.87	11.36	130.72	49	7.93	7.85
2016	369.5	125	11.60	14.29	2160.4	1019	13.82	13.82	101	43	6.96	6.11
2017	694.5	133	12.34	14.01	3348.2	1054	14.30	14.36	38.55	27	4.37	4.37
2018	632.1	149	13.82	13.73	5133.8	1098	14.90	14.90	75.87	36	5.83	4.96
2019	1139	145	13.45	13.45	3623.7	939	12.74	12.79	173.87	38	6.15	5.56
2020	474.4	107	9.93	9.93	4917.2	788	10.69	10.69	83.79	38	6.15	6.15
(e)	**Social Media**				**InsurTech**				**Mobile Advertising**			
Year	**$M**	**NI**	**DI**	**DP**	**$M**	**NI**	**DI**	**DP**	**$M**	**NI**	**DI**	**DP**
1991	0	0	0	0	0	0	0	0	0	0	0	0
1992	0	0	0	0	0	0	0	0	0	0	0	0
1993	0	0	0	0	0	0	0	0	0	0	0	0
1994	1	1	0.01	0.11	0	0	0	0	0	0	0	0
1995	15.3	4	0.04	0.22	0	0	0	0	0	0	0	0
1996	4	4	0.04	0.34	0	0	0	0	0	0	0	0
1997	16.5	3	0.03	0.45	0	0	0	0	0	0	0	0
1998	5	1	0.01	0.56	0	0	0	0	0	0	0	0
1999	225.9	20	0.22	0.67	0	0	0	0	0	0	0	0
2000	331.9	36	0.40	0.79	1.6	2	0.12	0	13	4	0.42	0

2001	33.6	13	0.14	0.90	11.1	1	0.06	0	0	0	0	0
2002	28.4	9	0.10	1.01	0	0	0	0	0	0	0	0
2003	72.6	16	0.18	1.12	0	0	0	0	0	0	0	0
2004	83.8	26	0.29	1.23	0.025	1	0.06	0	1.68	3	0.31	0.44
2005	181.4	56	0.62	1.35	0	0	0	0	41.46	5	0.52	0.87
2006	662.3	132	1.46	1.46	0	0	0	0	15.7	8	0.84	1.31
2007	1289	267	2.95	2.81	33.55	4	0.24	0.40	64.54	12	1.26	1.74
2008	1456	304	3.36	4.16	34.55	4	0.24	0.79	89.98	16	1.67	2.18
2009	932.9	292	3.23	5.51	0.1	1	0.06	1.19	71.55	25	2.62	2.62
2010	1048	458	5.06	6.87	16.2	7	0.42	1.59	122.16	37	3.87	5.10
2011	5258	702	7.76	8.22	20.08	9	0.54	1.98	287.69	53	5.54	7.59
2012	1711	894	9.88	9.57	115.04	19	1.14	2.38	157.58	60	6.28	10.08
2013	2416	1011	11.17	10.92	161.90	38	2.28	2.78	257.88	87	9.10	12.57
2014	3607	1111	12.27	12.27	233.84	53	3.18	3.18	341.66	144	15.06	15.06
2015	3829	925	10.22	11.08	645.07	96	5.75	7.13	1640.01	127	13.28	13.28
2016	4221	680	7.51	9.89	1108.70	163	9.77	11.08	578.72	113	11.82	11.44
2017	4978	567	6.26	8.70	855.17	258	15.46	15.04	1664.38	85	8.89	9.60
2018	5693	577	6.37	7.50	2111.69	317	18.99	18.99	655.87	84	8.79	7.76
2019	3071	479	5.29	6.31	3413.6	326	19.53	19.53	2100.33	54	5.65	5.92
2020	4070	463	5.12	5.12	4105	370	22.17	22.17	308.26	39	4.08	4.08

Table 2. Remote-science dataset and calculations: NC – BP as annual Number of Citations (out of top 10,000 cited papers), DI – Disruption Index, DP – Disruption Pattern.

	Geophysics			Economics			Psychology			Mathematics			Statistics		
Year	NC	DI	DP	NC	DI	DP	NC	DI	DP	NC	DI	DP	NC	DI	DP
1983	0	0	0	0	0	0	0	0	0	0	0		0	0	0
1984	56501	1.64	1.64	68609	1.39	1.39	133932	1.61	1.61	103087	2.63	0.00	65207	1.51	1.51
1985	44891	1.30	1.68	88480	1.80	1.58	169989	2.04	1.76	109353	2.79	0.00	59888	1.39	1.54
1986	59684	1.73	1.71	113929	2.31	1.76	218396	2.62	1.91	122387	3.12	0.00	92021	2.13	1.58
1987	55701	1.62	1.75	89363	1.81	1.94	178236	2.14	2.06	158775	4.05	0.00	98744	2.29	1.61
1988	56782	1.65	1.79	107223	2.18	2.13	223153	2.68	2.22	102338	2.61	0.00	100781	2.33	1.65
1989	63176	1.83	1.82	107848	2.19	2.31	179613	2.16	2.37	113004	2.88	0.00	83866	1.94	1.69
1990	64015	1.86	1.86	134305	2.73	2.49	227950	2.74	2.52	104284	2.66	0.00	74304	1.72	1.72
1991	57513	1.67	1.90	140111	2.85	2.68	283251	3.40	2.67	94976	2.42	2.42	79333	1.84	1.76
1992	54241	1.57	1.94	147895	3.00	2.86	236421	2.84	2.83	140463	3.58	2.56	90935	2.10	1.79
1993	56442	1.64	1.97	138006	2.80	3.05	211271	2.54	2.98	104555	2.67	2.69	78930	1.83	1.83
1994	69230	2.01	2.01	133639	2.71	3.23	236321	2.84	3.13	108317	2.76	2.83	112085	2.59	2.14
1995	71481	2.07	2.26	169738	3.45	3.41	264028	3.17	3.28	116305	2.97	2.97	173198	4.01	2.45
1996	82100	2.38	2.52	157487	3.20	3.60	259574	3.12	3.44	136777	3.49	3.47	116131	2.69	2.75
1997	71582	2.08	2.78	171403	3.48	3.78	303652	3.65	3.59	135555	3.46	3.98	92579	2.14	3.06
1998	107409	3.12	3.03	191891	3.90	3.96	311523	3.74	3.74	157149	4.01	4.48	129379	2.99	3.37
1999	105321	3.06	3.29	200677	4.08	4.15	281170	3.38	4.72	195631	4.99	4.99	127415	2.95	3.68
2000	138803	4.03	3.54	208998	4.24	4.33	474497	5.70	5.70	160584	4.10	4.75	149329	3.46	3.99
2001	132024	3.83	3.80	222252	4.51	4.51	414257	4.97	5.40	155206	3.96	4.50	185877	4.30	4.30
2002	147422	4.28	4.05	218640	4.44	4.53	376938	4.53	5.11	146006	3.72	4.26	161106	3.73	4.38
2003	140699	4.08	4.31	231556	4.70	4.55	431470	5.18	4.81	161520	4.12	4.02	164439	3.81	4.45
2004	157287	4.56	4.56	197369	4.01	4.56	376043	4.51	4.52	143296	3.66	3.77	166596	3.86	4.53
2005	157355	4.57	4.56	225431	4.58	4.58	307391	3.69	4.23	137769	3.51	3.53	191510	4.43	4.61
2006	157311	4.56	4.55	179899	3.65	4.29	323287	3.88	3.93	143345	3.66	3.28	167355	3.87	4.68
2007	158110	4.59	4.55	195325	3.97	4.00	368246	4.42	3.64	139307	3.55	3.04	183710	4.25	4.76
2008	158367	4.60	4.54	190637	3.87	3.71	283121	3.40	3.34	111112	2.83	2.80	150811	3.49	4.83
2009	146080	4.24	4.54	180928	3.67	3.42	255809	3.07	3.05	137174	3.50	2.55	212140	4.91	4.91
2010	156218	4.53	4.53	150149	3.05	3.13	253722	3.05	2.75	104091	2.66	2.31	203344	4.71	4.48
2011	139427	4.05	4.14	134420	2.73	2.84	194775	2.34	2.46	92555	2.36	2.06	165523	3.83	4.05
2012	129643	3.76	3.74	108446	2.20	2.55	138333	1.66	2.17	65988	1.68	1.82	139101	3.22	3.62
2013	118833	3.45	3.35	83253	1.69	2.26	123898	1.49	1.87	56324	1.44	1.58	88941	2.06	3.19
2014	100262	2.91	2.95	65339	1.33	1.98	104344	1.25	1.58	46917	1.20	1.33	138181	3.20	2.76
2015	71853	2.09	2.55	60250	1.22	1.69	63875	0.77	1.28	41738	1.06	1.09	116035	2.69	2.34
2016	61249	1.78	2.16	39524	0.80	1.40	38610	0.46	0.99	21961	0.56	0.85	46493	1.08	1.91
2017	35370	1.03	1.76	26710	0.54	1.11	40541	0.49	0.69	19735	0.50	0.60	49527	1.15	1.48
2018	27666	0.80	1.37	20404	0.41	0.82	18838	0.23	0.40	14024	0.36	0.36	38908	0.90	1.05
2019	16144	0.47	0.97	12141	0.25	0.53	8848	0.11	0.11	6639	0.17	0.17	18981	0.44	0.62
2020	19859	0.58	0.58	11836	0.24	0.24	14368	0.17	0.17	11767	0.30	-0.02	8262	0.19	0.19

Table 3. Tech-science dataset and calculations: NP – BP as annual Number of Peer review papers published, DI_{np} – Disruption Index based on NP as Base Parameter, DI_{ht} – Disruption Index calculated as hi-tech DI (BP is number of investments).

	Quantum Computing			*Artificial Intelligence*		
Year	**NP**	**DI_{np}**	**DI_{ht}**	**NP**	**DI_{np}**	**DI_{ht}**
1991	0	0.0%	0.0%	622	0.7%	0.0%
1992	1	0.0%	0.0%	650	0.7%	0.0%
1993	2	0.0%	0.0%	618	0.7%	0.0%
1994	0	0.0%	0.0%	598	0.6%	0.0%
1995	9	0.2%	0.0%	626	0.7%	0.0%
1996	8	0.2%	0.0%	656	0.7%	0.0%
1997	12	0.3%	0.0%	619	0.7%	0.0%
1998	25	0.6%	0.0%	691	0.7%	0.0%
1999	33	0.8%	0.0%	786	0.9%	0.0%
2000	42	1.0%	0.0%	840	0.9%	0.1%
2001	65	1.6%	0.0%	983	1.1%	0.1%
2002	60	1.4%	1.0%	1170	1.3%	0.1%
2003	78	1.9%	0.0%	1220	1.3%	0.1%
2004	90	2.2%	0.5%	1300	1.4%	0.1%
2005	103	2.5%	0.0%	1640	1.8%	0.1%
2006	105	2.5%	0.5%	1530	1.7%	0.2%
2007	107	2.6%	0.0%	1720	1.9%	0.3%
2008	129	3.1%	1.0%	1830	2.0%	0.4%
2009	128	3.1%	0.5%	2070	2.2%	0.4%
2010	128	3.1%	1.0%	2230	2.4%	0.7%
2011	132	3.2%	1.0%	2600	2.8%	1.1%
2012	159	3.8%	1.0%	2730	3.0%	2.1%
2013	175	4.2%	2.5%	3170	3.4%	3.5%
2014	183	4.4%	8.5%	3550	3.8%	5.2%
2015	209	5.0%	7.5%	3960	4.3%	7.9%
2016	235	5.7%	4.0%	4380	4.7%	11.2%
2017	307	7.4%	10.0%	5720	6.2%	14.6%
2018	384	9.2%	16.4%	8330	9.0%	17.2%
2019	530	12.7%	17.4%	12400	13.4%	17.5%
2020	718	17.3%	27.4%	23200	25.1%	16.9%

2.2. Calculation of the Disruption Index

Previous studies proposed disruption indices that use scientific citations as proxy for influence. As a result, their approach could not be directly applied to hi-tech, as it lacks citations. Moreover, their approach is partially subjective, as it relies on the decisions of the writers that add references to their papers. To avoid these pitfalls, our new Disruption Index (DI) is behavioral in nature, and calculates the relative activity in each time period as proxy for disruption:

$$DI_i^f = \frac{BP_i}{\sum_{j=1}^{p} BP_j}$$

$\mathbf{DI_i^f}$= **Disruption Index** for field **f** (within hi-tech or science) in year **i**

$\mathbf{BP_i}$= **Base Parameter** (e.g., number of investments) in year i

p = Number of years in this period

The Base Parameter (BP) can vary between fields, as long as it represents the underlying behavior, and is not too susceptible to outliers. **The Base Parameter for the hi-tech DI is the number of investments within each of the fields listed above, regardless of their dollar size.** We chose this BP since very large investments mask the actual market behavior. For example, 100 investments of $2M each in a certain year are not equal, in terms of behavior, to a single investment of $200M, although the total dollar amount is the same.

Science traditionally evaluates applications according to their citations. We find this parameter problematic for evaluating the progress of science since it highlights "stars" (equivalent to huge investments). We address science development as an ecosystem of research and disciplines rather than a series of individual ingenious publications. Therefore, we took the **BP** for the science fields as either the number of articles that were published within a discipline every year (for tech-science) or only the 10,000 most cited publications in the discplines, distributed again by years (for remote-science). After choosing the right BP, a DI can be easily calculated for all fields, thereby allowing a seamless comparison between the hi-tech and science fields and their internal categories.

2.3. Calculation of the Disruption Pattern

Results of the calculated DI show a four-stage pattern in hi-tech and science. It includes the (1) Exploration, (2) Exploitation, (3) Plateau, and (4) Exhaustion stages. To quantify this pattern, we built a Disruption Pattern) DP) for each field, which simplifies the DI by representing each of the four stages as straight lines:

$$DP_i^f = DP_{i-1}^f + \frac{DI^f_{p(\text{ period } (i))} - DI^f_{p(\text{ period } (i-1))}}{p(\text{period}(i)) - p(\text{period}(i-1)) + 1}$$

$\mathbf{DP_i^f}$= **DP** for field f in year i. for year 1, DP=DI.

p(period(i)**)** = The last year of the period (1-4) to which year i is related

$\mathbf{DI^f_{p(\text{period } (i))}}$= **DI** (as defined above) for field f in the last year of the period to which year i is related.

Stage 1 starts when the data begins. Its transition into stage 2 marks the disruption year, when Exploration abruptly shifts to Exploitation. This transition is set by maximizing the correlation between DI and DP:

$$DY^f = argmax_y^f \{\rho\left(DI^f, DP^f\right)\}$$

$\mathbf{DY^f}$= **Disruption Year** for field **f**

$\boldsymbol{\rho}\left(\mathbf{DI^f, DP^f}\right)$= Correlation between DI and DP in field f

$\mathbf{argmax_y^f}$= Year y that maximizes the value of the given function, for field f

The transition between stages 2 and 3 (Exploitation to Plateau) occurs at the DI maxima value, whereas the transition to stage 4 (Plateau to Exhaustion) begins when the DI value drops by 5% or more. Not all fields show all four stages – some may still be in an earlier stage.

3. Results

Data from hi-tech and science show a similar four-stage pattern with some variations: The**hi-tech** dataset is based on the number of investments in 15 startup categories between 1991-2020 (Fig. 1): Cloud Storage, Mobile Apps, Quantum Computing, Artificial Intelligence, Big Data, Virtual Reality, Blockchain, Cryptocurrency, E-Learning, 3d Printing, Internet of Things, SEO, Social Media, Insurtech, And Mobile Advertising. The categories were chosen to show a wide range of behaviors. While the Dollar amount of investments is an obvious proxy for the activity in each category, it is highly affected by outliers (i.e., substantial investment), inflation, and the inflow rate of funds to the market. On the other hand, the number of investments, regardless of size, can serve as a proxy for market-wide activity, and a tool for identifying disruption. Therefore, the new DI was based on the number of investments normalized by their total number for the analyzed period.

In the first 8-12 years, the hi-tech DI slowly increases (i.e., Exploration stage) until a particular year when values begin to grow exponentially over1-5 years (Fig. 1; Exploitation stage). This trend change marks a disruption. The growth culminates into a 1-3 year of relatively constant DI values (Plateau stage), followed by a sharp decrease (Exhaustion stage). This four-stage pattern appears in three groups (Fig. 1). Disruption of the light blue group (2009) predates the brown one (2012) and decreases faster. Both groups show the same DI maxima. In the gray group, disruption occurred during 2013-2014, followed by a sharp DI climb to almost doubling the values of the other groups.

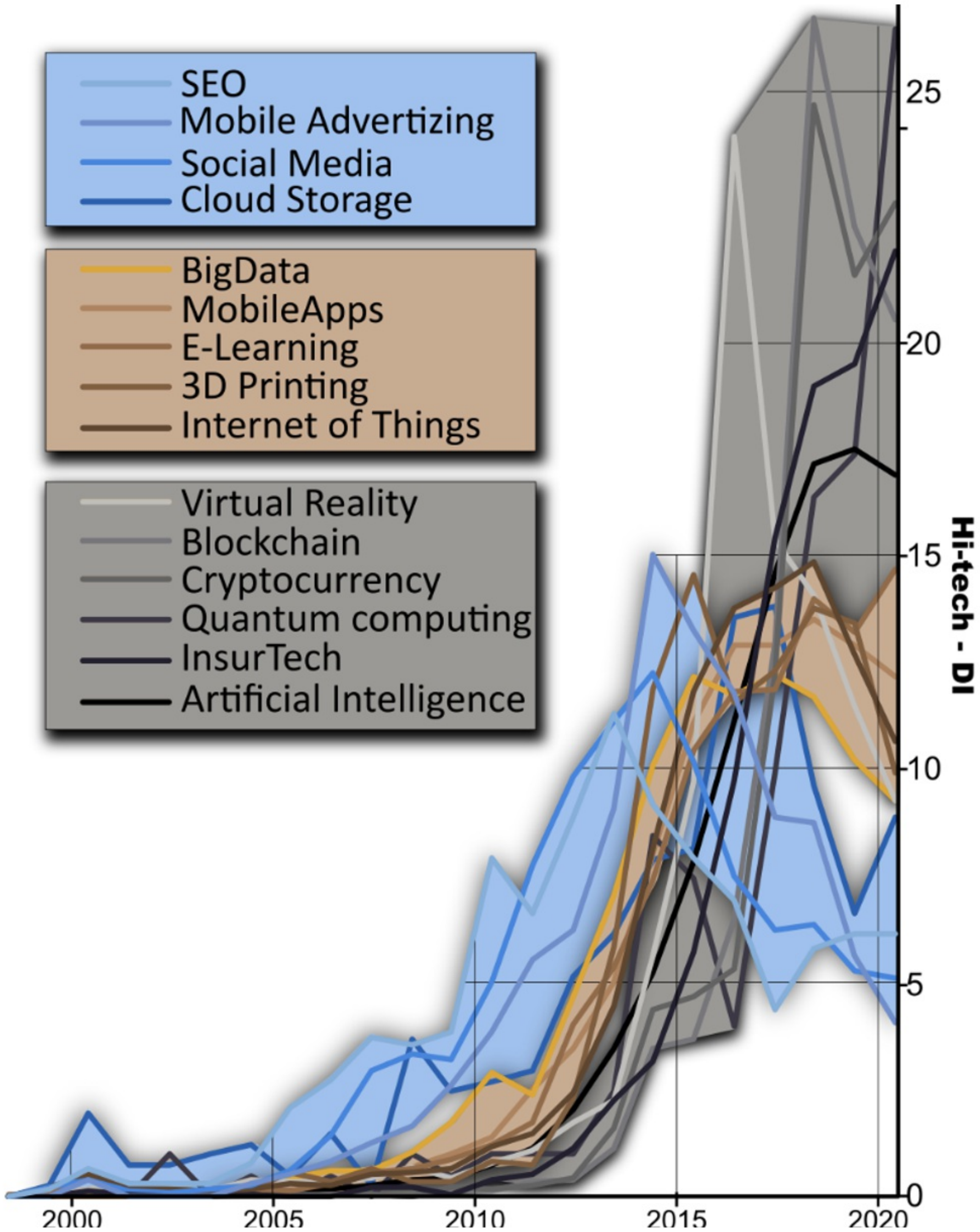

Figure 1. Disruption Index (DI) of 15 Hi-tech categories vs. time (data in Table 1).

The **science** DI represents two fields. DI of the technological-related science (tech-science; light blue in Fig. 2) is calculated based on the number of publications in Quantum Computing and Artificial Intelligence between 1991-2020. This DI behaves similarly to the hi-tech Exploration and Exploitation stages – it gradually increased between the late 1990s and early 2010s, and sharply steepened in 2017-2018. These young disciplines have not yet reached a Plateau.

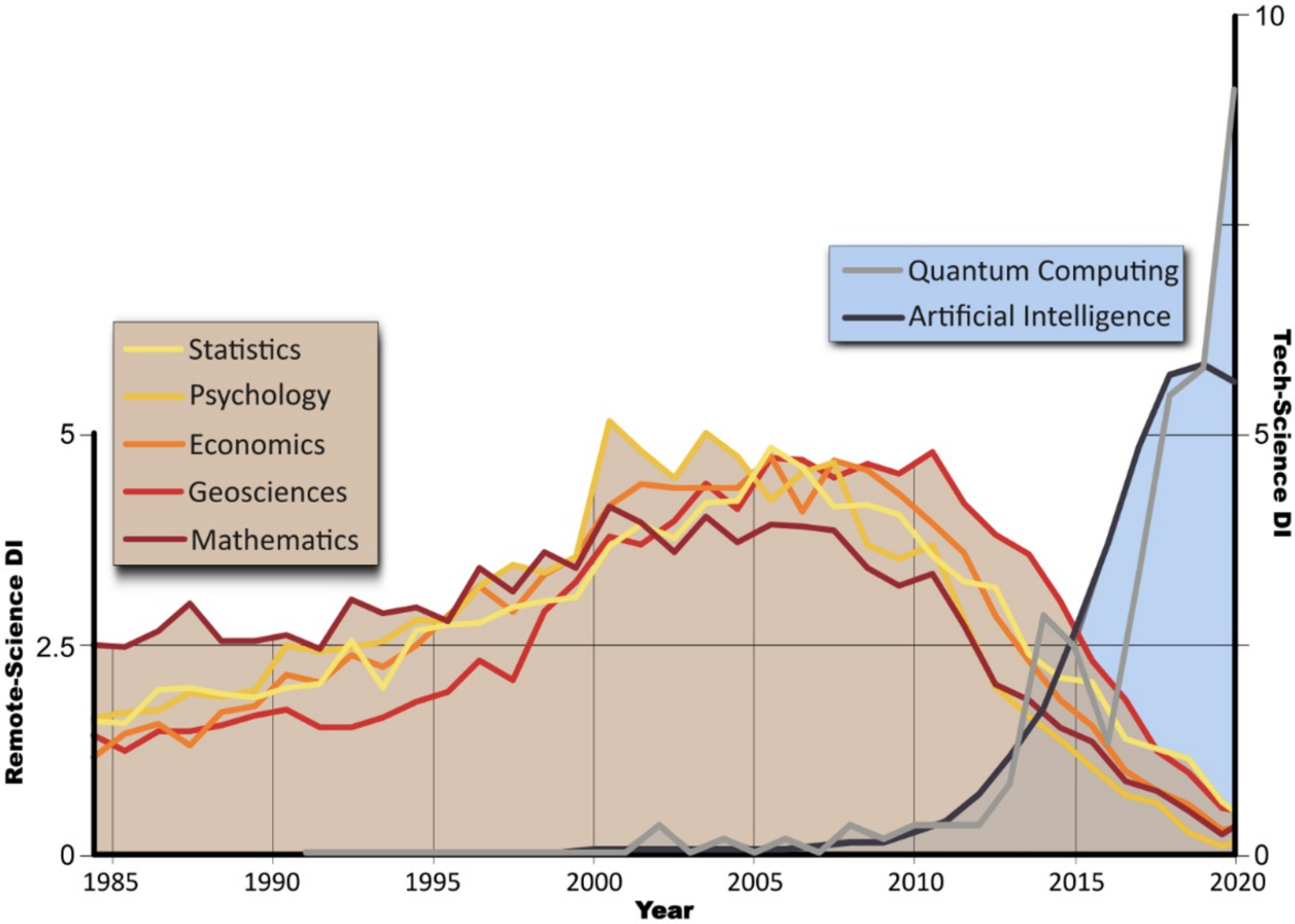

Figure 2. DI of remote-science (brown, left axis) and tech-science (light blue, right axis) disciplines (data in Tables 2, 3, respectively).

DI of less the technological disciplines (remote-science; light brown in Fig. 2) is calculated based on the 10,000 most cited peer-reviewed papers between 1984-2020 in Geosciences, Economics, Psychology, Mathematics, and Statistics. This DI citation percentage expresses the assimilation level of research insights (a common measure of academic impact) and the financial investment in research and education (e.g., infrastructure and training of graduate students). The DI shows a four-stage pattern, similar to those described above (Figs. 1, 2), despite the weak relations between its five disciplines. The citation percentage gradually increased from the 1980s to the mid-1990s (i.e., Exploration), then grew faster over ~5-year (i.e., Exploitation). The Plateau lasted between 2000-2010, followed by a DI decline to values lower than the initial ones (i.e., Exhaustion). Correlations between the DI of the five disciplines yield values of 67%-97% (Table 4). All 20 categories examined show high correlations between their respective DI and the four-stage Disruption Pattern. The average DI-DP correlation is 0.98 for the hi-tech categories and 0.96 for remote-science.

Table 4. Correlations between indices of relative citations, 1984-2020.

	Geosciences	Economics	Psychology	Statistics	Mathematics
Geosciences	1.00	0.91	0.78	0.92	0.66
Economics	0.91	1.00	0.95	0.97	0.87
Psychology	0.78	0.95	1.00	0.92	0.94
Statistics	0.92	0.97	0.92	1.00	0.85
Mathematics	0.66	0.87	0.94	0.85	1.00

4. Discussion

Despite the differences between the various fields examined, the data show their behavior to be similar. The four-stage pattern identified here appears in both hi-tech and science, with variations in the duration and intensity of modifications (Fig. 3). During the Exploration stage the steady and moderate growth in **hi-tech** and **tech-science** DI (Figs. 1, 2) indicates the market cautiously seeks disruption without drastic deviations. Once disruption occurs, both fields quickly identify and evaluate its potential while bursting into action. The shorter Exploration stage and sharper Exploitation ascend in the gray hi-tech group show that disruption identification and evaluation improved over time. However, the more Deep-Tech the discipline is, the faster tech giants exploit its disruption once it occurs, and attract much of the activity. This drastically decreases the number of investments, leading to the Plateau stage. The tech-science gains directly and indirectly from the increasing number of investments and becomes more productive. Based on the four-stage pattern identified here, Artificial Intelligence, Quantum Computing, and other tech-science disciplines are expected to reach their Plateau stage in 2-5 years (Fig. 3).

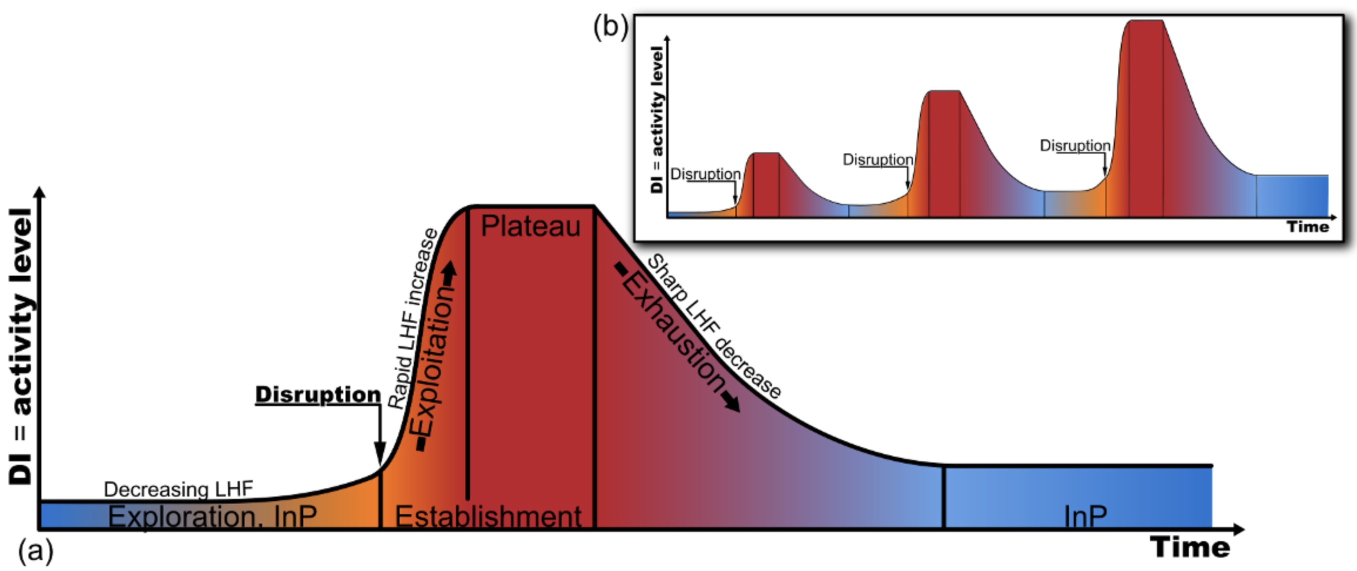

Figure 3.Hi-tech and science develop through ongoing InP with occasional Disruptive leaps. Schematic illustration of conduct during (a) one four-stage pattern cycle, and (b) its expected progression over time. InP - Incremental progression, LHF - Low-Hanging Fruits. Warm and cold colors represent the market/science activity level.

All **remote-science** disciplines show similar behavior in both the duration of the stages and their intensity, which is peculiar (Fig. 2). Why would the distant disciplines of Geosciences, Economics, Psychology, Mathematics, and Statistics show a synchronized behavior when each undergoes substantial modifications over the years? A possible explanation is that they all are equally more sensitive to exogenous processes than endogenous ones. During the exploration stage, citations are influenced by many intradisciplinary directions and trends, but at a certain point, the citations percentage sharply steepens in all disciplines. Similar to the hi-tech domain, the high citation percentage during exploitation represents a sudden expansion of directions opened by disruptive event or events. The Plateau begins when citations reach a Status Quo, i.e., certain studies are repeatedly cited as the pioneering of the discipline. This behavior is equivalent to the takeover by tech giants. The newer cited studies form finer variation superimposed on the Plateau (Fig. 2). When the pioneering studies become less relevant, the Plateau ends and the Exhaustion stage begins while the disciplines await new Internal breakthroughs. Nonetheless, the highly synchronized behavior of the distant disciplines suggests they represent the state of science in general. While universities and funding sources acknowledge that science has reached stagnation and encourages potential breakthroughs from within the discipline, our data suggest that the eagerly awaited disruption will most likely arrive from exogenous events.

The main driver for this systemic behavior is probably technology. In the late 1990s, the Internet became a major force that changed research activity. Scientists moved from citing printed papers (from libraries, photocopies, and pre-prints sent by snail mail) to searching them online. This may have shifted the remote-science disciplines from Exploration to Exploitation (Figs. 2, 3). However, after about five years, science reached another plateau, and it could be argued that accessibility promoted by the Internet only shifted science from one plateau to another while it remained stagnant.

The end of the Plateau (2008-2010) may represent the immersion stage in which publications build their influence. Their delayed influence further stresses how InP inhibits the citation of disruptive papers. However, the Exhaustion stage began almost simultaneously in all disciplines, pointing at exogenous circumstances. We attribute this shift to improvements in computing power which allowed better data acquisition and stronger analytical tools able to crunch considerably larger datasets. These exogenous technological advancements made the frequently cited pioneering studies obsolete. Science entered a new exploration stage where the analytical tools created new low-hanging fruits to be harvested. Scientists rely more on data and quantitative models, and less on established theories and conceptual ideas. This 10-15 years trend questions the effectiveness of the citation system widely used for evaluating studies for funding and promotions. Today, the sweeping introduction of Artificial Intelligence and Machine Learning tools will likely create another systemic change across all scientific disciplines. Again – an exogenous influence.

4.1. Why did the prevailing InP methodology lose its effectiveness?

The InP methodology is most effective during the **Exploration** and **Plateau** stages, when basic knowledge is being built. For example, when mapping and describing terra incognita in any discipline and understanding the relations between its dominant processes. InP is effective in these cases since knowledge maps are still underdeveloped, and there are many low-hanging fruits to discover. Nevertheless, when the low-hanging fruits become scarcer, and the discipline moves to an

Exhaustion stage, InP becomes less productive.

In InP, processes transforming status A to B are described using catalysts and inhibitors. Such ***Causal Logic***, coupling a cause with an outcome, underlies most studies and the training of future scientists. For example, the influence of a compound on a biological process or a chain reaction induced by an underwater earthquake. However, as scientists specialize in their discipline (i.e., dig deeper into an InP process), they realize that Causal Logic can only provide a partial explanation, and that deduction by elimination does not necessarily lead to an acceptable solution. To bridge over the gap in understanding, studies simplify the cases by neglecting components or reducing dimensions. These simplifications fit the InP specialization, not the phenomenon under investigation. We suggest that most case studies examined in science are derived from a larger multi-complement, multi-dimensional complex system of interweaving processes that dynamically affect each other. However, the InP and traditional Causal Logic only work in “Silos” (i.e., confined to the InP universe) and cannot deal with several components simultaneously.

Here are some examples. The climate crisis brought **Geosciences** to the limelight but caught the scientists and discipline unprepared. Most Geoscientists focus on subdisciplines, yet a concept defining Earth as a ***Complex System*** is only starting to form (Siegenfeld and Bar-Yam, 2020; Author et al., 2023). Yet, there are currently no suitable quantitative tools for analyzing the data of a Complex System. While data collection increases over time, predictive models based on this data are not calibrated to the growing occurrence of extreme events (e.g., mega-floods, storms, droughts). Hence, current models are still far from providing accurate predictions of the climate change pace, and they struggle to integrate extreme events and evaluate the variability of relevant parameters.

The thought framework for Micro-**economic Theory** has been mostly stagnant for several decades. The basis for consumer decision-making in Microeconomics has not shifted far from its origins in Tversky and Kahneman’s studies dating 40-50 years ago, as evidenced by the following. According to Google Scholar, out of a total of 191,000 articles mentioning or written by Tversky and Kahneman, 8.8% (16,800) appeared in the last three years (2020-2022).

InP promotes a non-disruptive and less-exploratory science, which relies on the availability of low-hanging fruits (Fig. 3). Its ineffectiveness leads to one of the greatest crises in all scientific disciplines today. Institutes and funding agencies that understand the crisis and encourage cross- and multi-disciplinary studies on the individual scientist level (yet, these scientists are products of the InP specialization process). They also began to cautiously question the fixated and archaic disciplinary division (yet, at the same time, reject projects that jump too many steps ahead). Walls between disciplinary teaching programs begin to (slowly) break. This positive approach is insufficient to prevent science from slowing down, since most scientists still follow the InP methodology, which hinders disruptive conceptual leaps.

On top of that, although universities primarily promote scientific findings, they await to monetize innovations and inventions. Therefore, they implement a supportive innovation strategy to drive research into business-related areas. While this approach may catalyze economic gains, it merely invests in gradually improving existing research that follows InP and Causal Logic methodologies. It does not provide a Disruption mindset or infrastructure to researchers.

4.2. Can science develop endogenous disruptive seeds?

The progress of science can therefore be described as an interplay between Disruptive scientific leaps on top of an ongoing InP (Fig. 3). InP bursts science into Exploitation when low-hanging fruits are abundant, but when they become scarce InP reacts with Exhaustion. InP does not form disruption itself. Still, only InP efforts have developed into a well-established research process that includes funding resources, publication infrastructure and collaboration frameworks. On the other corner, Disruptive research remains anecdotal and is only beginning to be recognized as a crucial force that pulls science forward. The dizzying pace at which the high-tech industry is advancing and creating Disruption is unmatched by universities and research institutions. Despite their efforts to promote innovation and entrepreneurship, universities do not produce considerable breakthroughs. Their main discoveries are made in relatively new areas where little research has been done so far, or data has not been collected in large quantities to date.

Substantial breakthroughs require the challenging of traditional conventions. In hi-tech, this disruptive approach creates breakthroughs, e.g., a new market category that profoundly shifts the daily routine to a new and unpredictable path. The Internet also exemplifies a phase transition (Fig. 1). Its intervention was not merely a technology as described in its early days. The Internet diverted the progress of an immense amount of systems and scientific disciplines to a path that was impossible to predict with pre-Internet knowledge. Science is cautious and its progress relies on knowledge that gradually builds. However, as extensive as pre-transition knowledge may be, it cannot reliably predict post-transition behavior since current "siloed" logic will likely break down, and new apparent causality will emerge.

Today there is no established methodology for creating Disruption in hi-tech (this could be an oxymoron). Nevertheless, the hi-tech industry developed a practical and powerful toolbox that only partially entered universities, mainly through the monetization of research. Decision makers in universities, funding agencies, and research institutes should adopt a venture capital approach to boosting new disciplines, and allowing research pivots (i.e., unexpected turns), based on the understanding of disruption activity and patterns, as manifested in the DI and DP measures. They need to encourage endogenous disruption by promoting a "startup mindset"; endorse exogenous disruption; support non-InP exploration directions; improve the identification of exploration-to-exploitation shifts and rapidly respond to disruption points as hi-tech does; implement a more holistic, Complex-Systems approach to research; improve the incentive to go beyond InP into Disruption; and reduce the heavy reliance on citations as indicators of research disruption potential. All these will help to accelerate scientific disruption, alongside the traditional InP and Causal Logic.

References

- Bhaskar, M., 2021. Human Frontiers: The Future of big ideas in an Age of small Thinking. MIT Press.
- Bhattacharya, J., Packalen, M., 2020. Stagnation and Scientific Incentives. National Bureau of Economic Research (NBER) Paper No. w26752.
- Bloom, N., Jones, C.I., Van Reenen, J., Webb, M., 2020. Are ideas getting harder to find? American Economic Review 110, 1104-1144.
- Bornmann, L., Devarakonda, S., Tekles, A., Chacko, G., 2020a. Are disruption index indicators convergently valid? The

comparison of several indicator variants with assessments by peers. Quantitative Science Studies 1, 1242-1259.

- Bornmann, L., Devarakonda, S., Tekles, A., Chacko, G., 2020. Disruptive papers published in Scientometrics: meaningful results by using an improved variant of the disruption index originally proposed by Wu, Wang, and Evans (2019). Scientometrics 123, 1149-1155.
- Collison, P., Nielsen, M., 2018. Science is getting less bang for its buck. The Atlantic.
- Ip, G., Stagnant scientific productivity holding back growth. Wall Street Journal.
- Min, C., Bu, Y., Wu, D., Ding, Y., Zhang, Y., 2021. Identifying citation patterns of scientific breakthroughs: A perspective of dynamic citation process. Information Processing & Management 58, 102428.
- Park, M., Leahey, E., Funk, R.J., 2023. Papers and patents are becoming less disruptive over time. Nature 613, 138-144.
- Shepherd, L., 2023. Why science has become less innovative, medium.com.
- Siegenfeld, A.F., Bar-Yam, Y., 2020. An introduction to complex systems science and its applications. Complexity 2020, 1-16.
- Wu, L., Wang, D., Evans, J.A., 2019. Large teams develop and small teams disrupt science and technology. Nature 566, 378-382.
- Xu, F., Wu, L., Evans, J., 2022. Flat teams drive scientific innovation. Proceedings of the national Academy of Sciences 119, e2200927119.