Review of: "Science desperately needs disruptive innovation"

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It's hard to write a review for an article that reaches a conclusion that I think is very likely true but does so using methods that I think are insufficient to reach its conclusion. After reading "Science Desperately Needs Disruptive Innovation" – a provocative title for an interesting paper by Uri Schattner and Moti Shater – that is the position I find myself. Avoiding a critique of the paper is tempting because of the agreement about the conclusion. But ironically, scientific stagnation happens partly because of such temptations, so I'll focus my review on my explanation for why I don't think the empirical work in the paper establishes the authors' conclusions.

The goal of the authors is to contrast the presence of "disruptive innovation" in the high-tech world (cloud storage, mobile apps, virtual reality, etc.), in computational technology (artificial intelligence, quantum computing) versus its lack in traditional old-school academic disciplines (economics, psychology, etc.). They call these three different sets of fields "high-tech," "tech-science," and "remote science," respectively.

Juxtaposing these disparate fields in a single paragraph or paper conjures an obvious point: Disruption in a centuries-old field like economics or psychology will undoubtedly look very different than in a recently introduced technology like crypto-currency, as will the means by which such disruption might happen.

In scientific fields, disruption might look like a new scientific framework that incorporates the old framework as a limiting case or useful approximation in the way that 20th-century relativistic and Newtonian mechanics are related. Or it might mean a replacement of the old paradigm altogether with a new one, the way that the heliocentric model of planetary motion replaced the geocentric model. Or the advance might survive alongside the old paradigm, such as the relationship in economics between the neoclassical perspectives on risk aversion and Kahneman-Tversky prospect theory. In any case, disruptive innovation in these fields does not mean the old ideas are entirely forgotten. Even Ptolemy's geocentric model with its epicycles is routinely referenced or cited in physics textbooks and elsewhere to give context to the importance of the heliocentric model. Newtonian physics is still taught to undergraduates as is the neoclassical theory of risk preference, and professionals in their fields use both.

By its very nature, disruptive innovation will have a different effect in technology fields. Fundamentally new ideas will create products or industries that entirely replace the function of older technologies, such as replacing rotary phones with digital ones. Or the disruption might result in demand for products or capacities that did not exist before the disruption, such as ubiquitous computing devices or cheap power. The old technologies, or lack of them, are forgotten so that it is impossible to imagine living without what replaced them.

The lesson of these reflections is that disruptive innovation will mean very different things in different contexts, and disruption measurement will therefore be context-dependent.

The considerable challenge the authors take on is to consistently measure the amount of disruptive innovation in these vastly distinct sets of fields. The authors construct a "disruption index" (DI) to estimate an annual time series in each discipline to accomplish their goal. The DI in each year is the proportion of a sum of quantity that the authors call a "base parameter." Their disruption index is scaled between zero and one, and since they define it as a ratio of two quantities with the same units, the index itself is unitless.

All of the action is in the choice of these base parameters. The conceit is that if these base parameters capture the nature of disruptive innovation specific and relevant to each field, then the DI index will consistently and comparably measure in these disciplines. While I admire the agenda that the authors have set for themselves, I do not believe they have solved their problem.

For the traditional scientific fields ("remote science"), the authors define the base parameter as citations in peer-reviewed papers over time to the top 10,000 cited articles published between 1984 and 2000. With this base parameter, the authors' disruption index is just the proportion of total citations to these papers that occur in each year between 1984 and 2020. This measure has a mechanical problem in that articles published in the earlier years of that range will have more opportunities to be cited than those published at the tail end. This by itself may explain the precipitous drop in the share of citations to those papers after 2010. A separate phenomenon – the sharp rise over time in the number of papers published in these fields and more citations to the literature per paper – creates a second mechanical problem in the opposite direction. In any case, with these mechanical biases, it is not possible to read these trends as evidence of a collapse in innovation in these fields.

For the "tech-science" disciplines (quantum computing and artificial intelligence), the authors define the base parameter underlying their disruption measure (DI) instead by the number of peer-reviewed papers published in those fields each year. This is a better measure of disruption than the citation proportion-based DI measure used for the traditional fields, as the large number of recent peer-reviewed papers about these technologies certainly reflects the rise in interest in those technologies over the past few years. But whether this increased interest by academics in these topics reflects actual disruption or something else requires an analysis of the papers' substance rather than just a count. Fads in science and technology are a well-known phenomenon, often generating considerable interest but without lasting impact on society. So for this field, the authors' measure is best considered a measure of interest and activity in these fields rather than disruption.

Finally, for the "hi-tech" fields where most of the work takes place outside academia and peer-reviewed journals (e.g., cloud storage, mobile advertising, 3D printing, etc.), the authors use the number of investments in start-up companies within each field in the Crunchbase dataset as the base parameter. The results show that a large fraction of the number of investments made between 2000 and 2020 occurred within the last five years in these companies. This is a strong indicator of growing interest in companies that use or deploy these technologies, but it is again unclear whether this indicates disruption. For instance, it's hard to say that companies pursuing quantum computing have successfully disrupted any industry. Whether growing interest translates into disruption is an open question. The fact that many investors have made many investments in start-ups working on the topic is not sufficient to establish disruption.

It should be clear from the discussion that each of these base parameters – and hence the authors' DI measures- aim to track different phenomena and that the theoretical constructs they measure are distinct from one another. So even were I to grant that these base parameters accurately convey the extent of disruption within each field, it is not correct to say that they constitute a measure that can be used to compare disruption across the three types of areas ("remote science," "tech-science," and "hi-tech").

The authors have produced some interesting facts in their paper. My strong suggestion is to reframe their paper and data analysis to respect the strengths and weaknesses of the data sets they analyze rather than implausibly claiming to have produced a statistic that can be used to measure disruption across such widely varying domains comparably.