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Readability affects scientific impact: Evidence from emerging technology discourses

Lennart Ante [1, 2, *]

[1] Blockchain Research Lab, Max-Brauer-Allee 46, 22765 Hamburg
[2] Universität Hamburg, Von-Melle-Park 5, 20146 Hamburg

[*] ante@blockchainresearchlab.org

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Abstract: This study examines how the readability of scientific discourses changes over time and to what extent readability can explain scientific impact in terms of citation counts. The basis is a representative dataset of 135,502 abstracts from academic research papers pertaining to twelve technologies of different maturity. Using three different measures of readability, it is found that the language of the abstracts has become more complex over time. Across all technologies, less easily readable texts are more likely to receive at least one citation, while the effects are most pronounced for comparatively immature research streams. Among the more mature or larger discourses, the abstracts of the top 10% and 1% of the most often cited articles are significantly less readable. It remains open to what extent readability actually influences future citations and how much of the relationship is causal. If readability indeed drives citations, the results imply that scientists have an incentive to (artificially) reduce the readability of their abstracts in order to signal quality and competence to readers—both to get noticed at all and to attract more citations. This may mean a prisoner dilemma in academic (abstract) writing, where authors intentionally but unnecessarily complicate the way in which they communicate their work.

Keywords: Readability; Citations; Scientific impact; Emerging technologies

1 Introduction

An essential aspect of academic research is to make the results available to other researchers and to the public in the form of publications so that, for example, the development of theory progresses, explorative analyses become public knowledge or existing literature is analyzed and summarized. Given that the number of new academic publications has continued to grow in recent years (Altbach and De Wit, 2018), it is ever more important to communicate the findings in an optimal way, for example by a concise title or abstract. In fact, scientific success has become tantamount to not just making the results available but getting them noticed and cited by other scholars (Lu et al., 2019). This paper investigates whether an article's citation success is linked to the style in which it is written or, more specifically, to its readability.

The assessment of text readability based on formal analyses of the composition of words and other language structures is a long-standing scientific discourse that has produced hundreds of different metrics and methods (Gazni, 2011). Importantly, the resulting "readability scores" are typically somewhat at odds with the concept of readability in everyday language: A high score usually means that a text is more difficult to understand, i.e. its comprehension requires a higher level of education – in other words, the text is *less* readable. Readability assessment is a useful tool to determine whether the style of a text accords with the (language) skills of its intended readers. At the present time, various studies exist that address the readability of scientific studies and discourses. Building on a sample of 709,577 abstracts published between 1881 and 2015, Plavén-Sigray et al. (2017) show that the readability scores of scientific texts have declined over time, i.e. texts are becoming easier to comprehend. However, this trend does not hold across all time periods, disciplines and sectors. For example, publications in marketing (Bauerly et al., 2006) and tourism (Dolnicar and Chapple, 2015) have become more complex over time. Lei and Yan (2016) find that the readability scores of abstracts in information science increased between 2003 and 2012.

As prior research shows, readability can significantly affect scientific impact in the form of citations. Dowling et al. (2018) analyze the abstracts of 3,229 articles published in *Economics Letters,* finding a positive relationship between readability scores and citations, while McCannon (2019) finds that citation counts are negatively related to readability scores in a sample of 579 high-impact articles published in the *American Economic Review*. Marino Fages (2020) analyzes 9,757 *NBER* working papers and finds that articles with high readability scores are more likely to be published in a top journal. In biology, biochemistry and chemistry, however, no significant relationship was found between readability and citation counts (Didegah and Thelwall, 2013).

This study aims to broaden the scientific discourse by assessing the readability of a large set of abstracts from publications on twelve emerging technologies over time and by analyzing the link between readability and citation counts. Emerging technologies are characterized by their radical novelty, fast growth, coherence, prominent impact, uncertainty and ambiguity (Rotolo et al., 2015). Several studies have recently focused on the identification, analysis and forecasting of emerging technologies. For example, scientometric indicators (H. Xu et al., 2021), keyword analysis (Joung and Kim, 2017), patent analysis (Kyebambe et al., 2017), machine learning (Lee et al., 2018), social media data (Li et al., 2019) and frameworks based on topic models (S. Xu et al., 2021) or deep learning (Zhou et al., 2021) have been proposed to identify or monitor emerging technologies. While the identification of research streams, technologies and concepts requires considerable effort, it may help researchers to explore and publish on emerging topics, and academic journals and conferences to explicitly target these topics in the hope to anticipate future breakthroughs. Given that emerging technologies can transform entire economic sectors, they are also a curial concern for policymaking. The early and accurate assessment of their likely impact is therefore of great value. Once an emerging technology has been identified, various actors can try to formulate their optimal strategies, be they policymakers, society, individuals, or academic journals.

The present analysis is based on representative publication samples of twelve technological discourses that are at different points of development and maturity: artificial intelligence (AI), big data, Internet of Things (IoT), virtual reality (VR), cloud computing, blockchain, edge computing, autonomous driving, wireless body area networks (WBANs), smart contracts, and digital twin. For a topic to be included in this list, the associated search term(s) had to produce at least 500 publications from the Web of Science (WoS), at least one of which dates back at least five years. Since too many topics matched these criteria, the results were filtered so as to obtain some variation in terms of age and the number of publications, yielding a somewhat arbitrary set of twelve technologies. Each sample is examined using the same methodology to ascertain whether similar characteristics and effects can be identified. If the technological discourses prove to be similar regarding the development of readability over time and regarding any association between readability and scientific impact, it may be possible to infer similar relationships and developments for other recent or future discourses.

The first goal of this study is to identify how the readability of technological discourse changes over time. For this purpose, three widely used readability measures are alternatively applied to the abstracts. Although the abstracts constitute only a small part of each publication, they may be considered representative of their respective papers because they are the most frequently read section of the text and because the style of the abstract tends to be consistent with the rest of each article (Hartley et al., 2003).

The second goal is to see how readability affects scientific impact in the form of citations and, in particular, whether any persistent patterns across the twelve discourses might allow for more general inferences, e.g. with a view to predicting highly influential scientific contributions. In the following, scientific impact is operationalized as the papers either 1) not receiving any citations at all, 2) being in the top 10% in terms of normalized citations in a particular field and year or 3) the top 1% in terms of normalized citations in a particular field and year. This differentiation should give some indication as to whether researchers should consider the readability of their output on (emerging) technology research as they try to maximize their scientific impact.

This study proceeds as following. Section 2 presents and discusses the publication and citation data (Section 2.1), the normalization of the citation data (Section 2.2), and the readability metrics (Section 2.3). In Section 3, any citations effects of readability are analyzed. Section 4 contains a discussion of the results, including some limitations (4.1) and avenues for future research (4.2). Section 5 concludes.

2 Methods and descriptive statistics

2.1 Publication and citation data

The publication and citation data were collected from the WoS. The twelve search queries listed in Table 1 were executed in January 2021. The search was restricted to the category *Article*, which means that only peer-reviewed articles, conference papers and book chapters were returned. Furthermore, only articles published by the end of 2020 were collected. The search query option *TS (=Topic*) was used, which returns all publications in the WoS that contain the search terms in their title or abstract. All articles without abstracts were dropped (~1-4% per stream). The citation counts refer to citations in the WoS database—which are significantly lower than, for example, *Google Scholar*, because the WoS lists only selected journals.

Table 1. Research streams, search terms and descriptive statistics.

				Citations			
Research stream	Search query *TS=(...)*	Number of articles	First mention	Mean	SD	Max	Share of uncited articles
Artificial intelligence	*"artificial intelligence*"*	30,473	1985	12.2	52.9	3,805	27.7%
Big data	*"big data*"*	26,615	1993	12.0	57.0	5,387	25.3%
Robotics	*robotics**	25,970	1985	19.2	56.6	2,103	17.4%
Internet of Things	*"internet of things*"*	21,799	2002	12.0	66.2	6,115	26.4%
Virtual reality	*"virtual realit*"*	20.286	1991	17.5	43.3	1,745	20.7%
Cloud computing	*"cloud computing*"*	18,344	2008	14.9	63.2	4,461	22.9%
Blockchain	*blockchain* OR "distributed ledger*"*	4,059	2014	8.75	29.1	995	34.8%
Edge computing	*"edge computing*"*	3,399	2002	12.6	41.7	906	31.5%
Autonomous driving	*"autonomous driving*"*	1,553	1993	11.0	45.8	1,298	31.9%
Wireless body area networks	*"wireless body area network*" OR WBAN*	1,553	1999	14.2	36.9	690	18.4%
Smart contracts	*"smart contract*"*	1,006	2001	10.1	40.6	997	33.8%
Digital twin	*"digital twin*"*	711	2004	6.8	22.7	711	39.7%

In the context of the literature data extraction, it is likely that some relevant articles are omitted by the search queries that consist of high-level phrases. However, the comparatively simple approach chosen here, in addition to the ease of replicating the analysis, most likely covers the vast majority of all relevant articles. Accordingly, also due to the fact that WoS does not include "all" existing articles on the particular topics, the data set(s) obtained cannot be described as complete but rather as representative.

A total of 135,502 articles were extracted. With 30,473 (22.5%) publications, AI is the largest of the twelve discourses. Jointly with robotics, it is also the oldest, the earliest publication dating back 36 years. The youngest research stream (six years) is blockchain technology, which, however, has the seventh largest number of publications. Across the board, 24.75% of the publications have not been cited to date. This proportion is higher for comparatively recent discourses—unsurprisingly, because there the publications have had less time in which to be cited. The area of wireless body area networks constitutes an exception in this regard, with only 18.4% of uncited articles. The smallest and second youngest stream deals with digital twin technology. It has the lowest average number of citations per publication (6.8) and the highest share of uncited articles (39.7%). Given that about 60% of the stream's articles were published only in 2020, this is not surprising.

Fig. 1 shows, for each research stream, the development of the average number of citations per article and year (red line, right-hand scale) and the number of publications per year (black line, left-hand scale). The younger discourses are evidently growing very quickly, while the older discourses, like AI, robotics and VR, have been growing rapidly since 2015. This will partly be due the fact that the overall output of scientific research has increased in recent years (Altbach and De Wit, 2018). Regarding the average number of citations per article and year, younger discourses show a steady decline, while the three oldest peaked around 2003. The low values in recent years are again attributable to the fact that younger publications have had less opportunity to be cited (Schubert and Braun 1986).

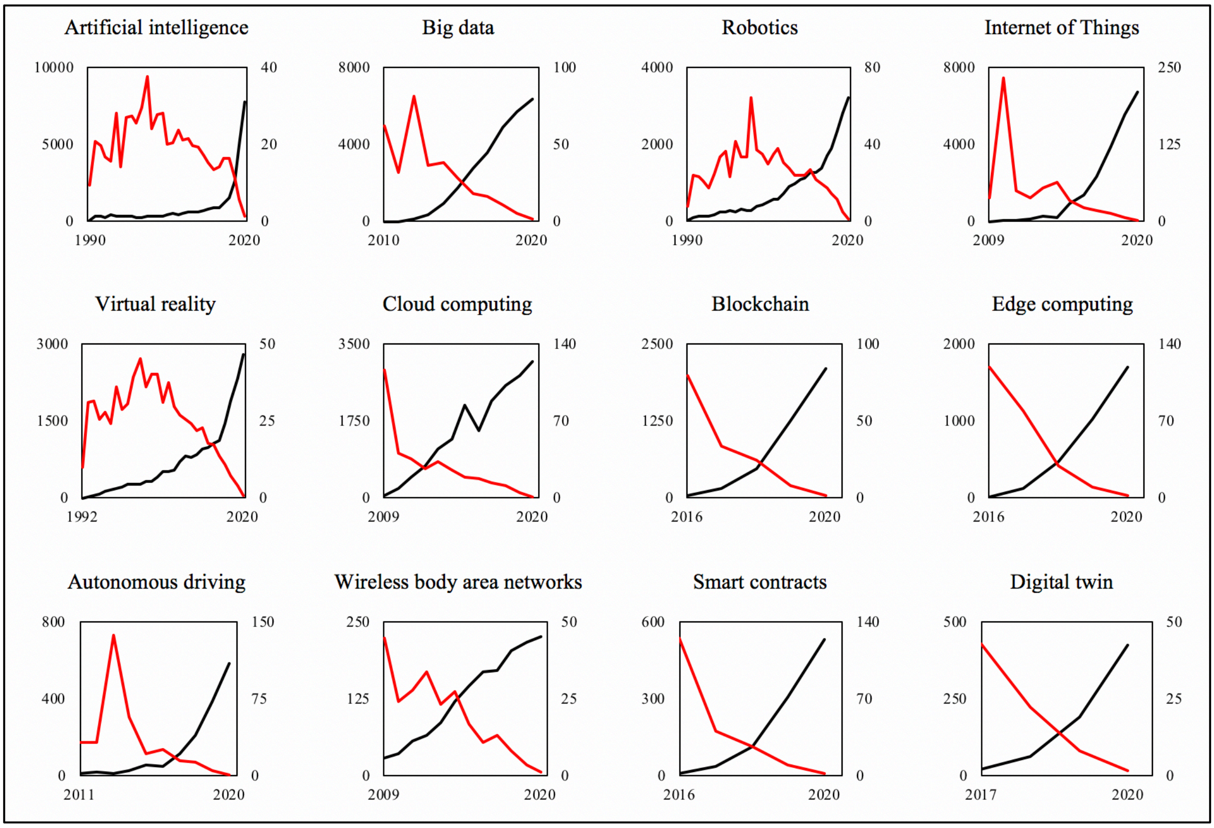

Fig 1. Number of citations and publications. The black lines show the number of publications per year (left-hand axis); the red lines refer to the mean number of citations that an article received each year (right-hand axis). Years with fewer than 10 publications are not shown.

2.2 Normalizing the citation data

Citation data are not normally distributed, as confirmed in Table 1. Furthermore, there are significant differences in citation habits between the individual scientific fields, and older articles benefit from the above-mentioned citation advantage. For these reasons, the normalization of citation data is common practice. We use the relative citation rate (RCR) described by Schubert and Braun (1986): An article's observed number of citations is divided by the expected citation rate, which equals the average number of citations of an article in the same technological discourse in a given year. Accordingly, the mean RCR of each discourse is always 1, as can be seen in Fig 2. The confidence intervals show that the variance of the citation counts declines as the scientific discourses develop over time.

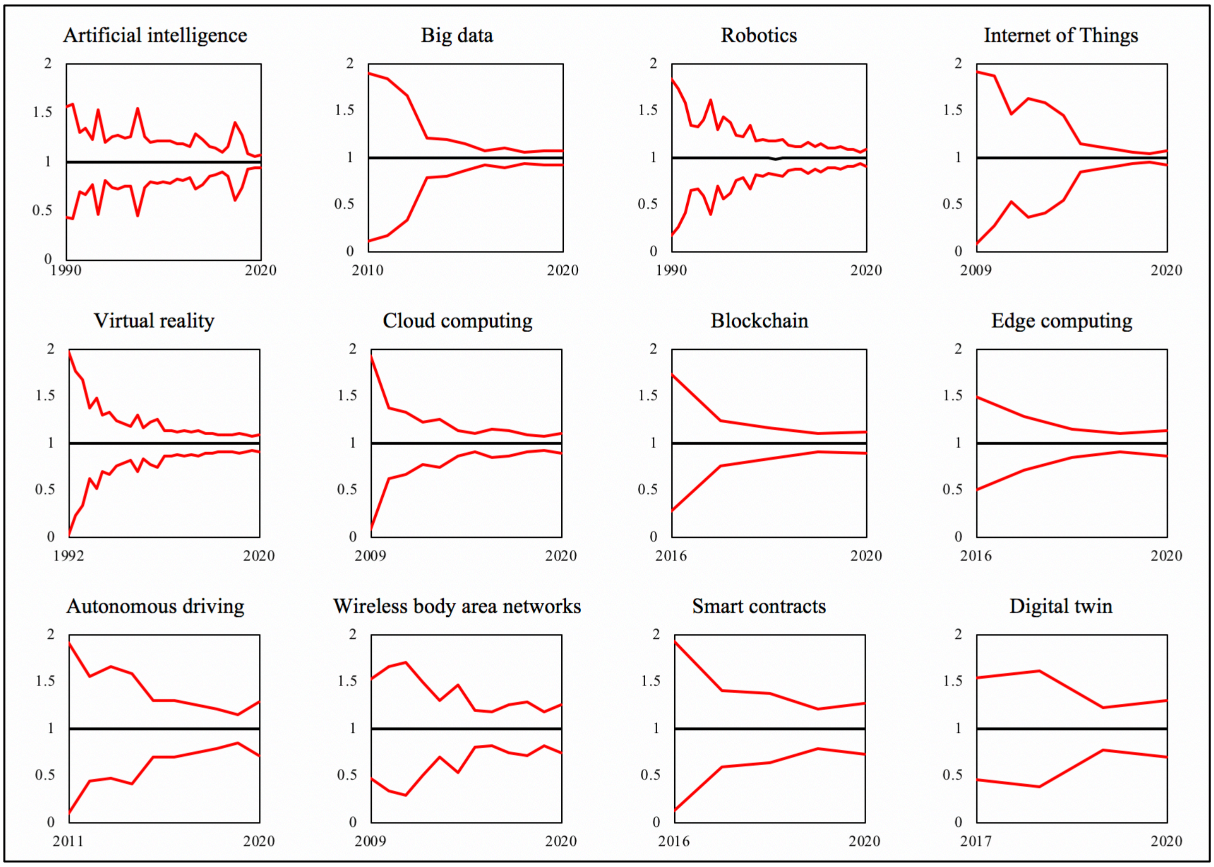

Fig 2. Relative citation ratios (RCRs) over time. The red lines show 95% confidence intervals for the RCRs. Only years with at least 10 observations are shown.

For further analysis, we create three dummy variables for each research stream. The first one indicates whether an article did not receive any citations at all; the second one indicates whether a publication is in the top 10% based of RCRs of a particular discourse; and the third one does the same for the top 1% of RCRs. These three variables are used as proxies for low, high, and highest scientific impact.

2.3 Readability analysis

The readability of the abstracts was analysed using the Python package *Readability 0.3.1* (*pypi.org/project/readability*). The package contains various readability measures for text data. To make the analysis both clear and robust, we choose three different readability measures that can all be interpreted in the same way—US grade levels. For example, a readability score of

15 (i.e. "15th grade") indicates that a university education would be required to comprehend a text, while a score of 5-6 indicates that Kindergarten-level education suffices to understand the text. The three measures are: 1) the *Flesch-Kincaid grade level (FKG)*, 2) the *Simple Measure of Gobbledygook (SMOG)*, and 3) the *Automated Readability Index (ARI)* (Flesch, 1948; Kincaid et al., 1975; McLaughlin, 1969; Senter and Smith, 1967). They are calculated as follows.

$$Flesch\text{-}Kincaid\ grade\ level = 0.39\left(\frac{total\ words}{total\ sentences}\right) + 11.8\left(\frac{total\ syllables}{total\ words}\right) \quad (1)$$

$$SMOG\ grade = 1.0430\sqrt{number\ of\ polysyllables\ \frac{30}{number\ of\ sentences}} + 3.1291 \quad (2)$$

$$Automated\ readability\ index = 4.71\left(\frac{characters}{words}\right) + 0.5\left(\frac{words}{sentences}\right) - 21.43 \quad (3)$$

Although the three readability measures use somewhat different input parameters, they tend to be positively correlated (e.g. Lei and Yan 2016). This is confirmed in Fig. 3, which shows the readability scores of the research streams over time. On average, the values of the ARI are about one point above those of the SMOG grade and about two points above the FKG. Given that the three metrics supposedly all refer to US grade levels, these differences are surprising. It should be noted, however, that the scores are above 14 throughout, which implies that the texts are best suited for readers with university education or even a PhD.

SMOG produces the most stable scores, especially in the fields of robotics, VR and WBANs, where the FKG briefly rises above the SMOG grade. Rising readability scores are evident in most streams—the abstracts have become more difficult to read. These results contrast with some of the literature (Plavén-Sigray et al., 2017). Scientific discourses on emerging technologies seem to exhibit peculiarities in their development that set them apart from the general scientific output.

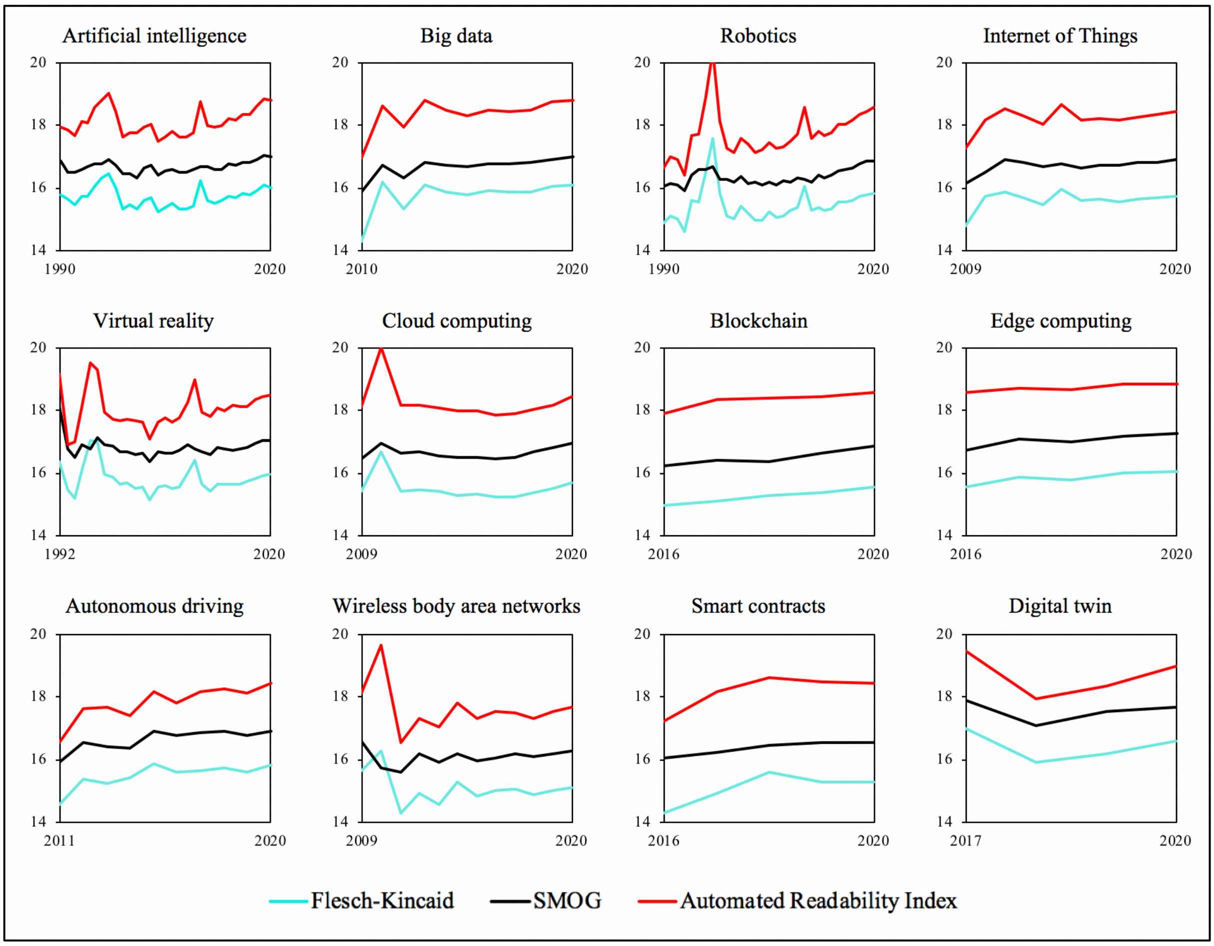

Fig 3. Abstract readability per research field. Only years with at least 10 observations are shown.

3 How readability affects scientific impact

While the last section presented statistics on individual metrics, these are now connected to identify whether readability affects scientific impact in the form of citations. Table 2 shows descriptive statistics for the three readability measures—in turn for all articles in each field and for the three subsamples (no citations, top 10% RCR, and top 1% RCR). Asterisks indicate significance in a two-sample t-tests with equal variances. In other words, they indicate whether the three subsamples differ significantly from the full sample in each research field.

The three readability measures yield quite similar scores across the twelve fields for the full samples (FKG: 15.0-16.5; SMOG: 16.1-17.6; ARI: 17.5-18.8). With a minimum average grade level of 15.0 (FKG for WBANs), the abstracts are clearly rather complex, requiring at least university education to be understood. For the four largest research streams, the readability scores of the 10% most often cited abstracts are significantly higher than in the reference group. This also applies to the top 1% for AI and robotics—the oldest discourses. For smaller discourses, significant differences are only found with respect to individual readability measures. For VR, blockchain, smart contracts and digital twin, we find that uncited articles are significantly easier to read than the average of all abstracts in each field. Overall, uncited articles on average are almost always easier or no more difficult to read than all articles, and the reverse holds for the abstracts of the top 10% and top 1% most widely cited articles.

Table 2. Readability and relative citation ratios per technology discourse. The table shows the average readability scores for the twelve technology discourses and subsamples based on (relative) citation count. For subsamples, the nominal p-values of a two-sample *t*-test are additionally shown. For the number of observations, see Table 1.

	FKG				SMOG				ARI			
	Full sample	Uncited articles	10% RCR	1% RCR	Full sample	Uncited articles	10% RCR	1% RCR	Full sample	Uncited articles	10% RCR	1% RCR
Artificial intelligence	15.8	15.8	17.1***	16.9***	16.8	16.8	17.0***	17.4***	18.4	18.4	18.9***	19.9***
		(0.108)	(0.000)	(0.000)		(0.318)	(0.000)	(0.000)		(0.186)	(0.000)	(0.000)
Big data	16.0	15.9	16.1**	15.8	16.8	16.8*	17.0***	16.8	18.6	18.5**	18.8***	18.4
		(0.242)	(0.018)	(0.315)		(0.090)	(0.000)	(0.624)		(0.033)	(0.000)	(0.378)
Robotics	15.6	15.6	16.1***	16.5***	16.5	16.5*	16.9***	17.2***	18.0	18.0	18.9***	19.6***
		(0.340)	(0.000)	(0.000)		(0.097)	(0.000)	(0.000)		(0.884)	(0.000)	(0.000)
Internet of Things	15.7	15.7	15.8***	15.7	16.8	16.8*	17.0***	17.0	18.3	18.3	18.6***	18.5
		(0.722)	(0.004)	(0.841)		(0.058)	(0.000)	(0.302)		(0.504)	(0.000)	(0.466)
Virtual reality	15.8	15.7***	15.8	16.2	16.8	16.6***	16.9	17.2**	18.2	18.1**	18.4***	18.9**
		(0.000)	(0.732)	(0.146)		(0.000)	(0.280)	(0.026)		(0.019)	(0.006)	(0.020)
Cloud computing	15.4	15.4	15.4	15.4	16.6	16.5*	16.7***	16.7	18.1	18.0	18.1	18.1
		(0.701)	(0.745)	(0.984)		(0.087)	(0.005)	(0.404)		(0.546)	(0.470)	(0.842)
Blockchain	15.4	15.2**	15.2	15.2	16.7	16.7*	16.7	16.8	18.4	18.2*	18.3	18.1
		(0.014)	(0.217)	(0.708)		(0.054)	(0.230)	(0.636)		(0.183)	(0.483)	(0.562)
Edge computing	16.0	16.0	16.0	15.9	17.2	17.2	17.3	17.3	18.8	18.7	18.9	18.6
		(0.535)	(0.734)	(0.916)		(0.572)	(0.321)	(0.787)		(0.303)	(0.594)	(0.740)
Autonomous driving	15.7	15.7	15.6	15.2	16.8	16.8	16.7	16.6	18.2	18.2	18.2	18.1
		(0.990)	(0.493)	(0.384)		(0.709)	(0.397)	(0.552)		(0.880)	(0.927)	(0.870)
WBAN	15.0	14.8	15.2	15.1	16.1	15.9*	16.4*	16.0	17.5	17.3	17.9	17.6
		(0.148)	(0.352)	(0.920)		(0.098)	(0.059)	(0.808)		(0.281)	(0.196)	(0.946)
Smart contracts	15.3	15.1**	15.4	15.2	16.5	16.7*	16.5	16.2	18.5	18.3*	18.6	18.6
		(0.049)	(0.723)	(0.949)		(0.081)	(0.914)	(0.632)		(0.083)	(0.581)	(0.849)
Digital twin	16.5	16.2**	16.7	16.8	17.6	17.4*	17.8	18.0	18.8	18.5*	19.1	19.0
		(0.045)	(0.394)	(0.770)		(0.065)	(0.532)	(0.625)		(0.085)	(0.432)	(0.882)

*, **, *** indicates a difference between the full sample and the respective subsample that is significant at the 10%, 5%, or 1% level (two-sample *t*-test).

Table 3 shows Pearson correlation coefficients and p-values for the three readability measures, for the variable RCR in general and for the three subsamples (no citations, top 10% RCR, and top 1% RCR). The four largest fields all return significantly positive correlations between RCR and the three different readability measures. Correlations for uncited articles across these four fields remain largely insignificant, while the top 10% and top 1% samples have significantly positive relationships with readability in most cases. For comparatively recent discourses, the correlations are largely insignificant when considering results across all three measures for the purpose of robustness.

In the next step, logistic regression models are estimated to gauge whether the scores from the three readability formulas affect the articles' scientific impact, specifically the likelihood of their falling into one of the three categories (no citations, top 10%, top 1%). In line with prior research on readability and scientific impact (e.g. Dowling et al. 2018), year fixed effects are included in the analysis. In addition to the entire sample, as a robustness check, we also investigate a reduced sample, which excludes all articles published in 2020. The aim is to reduce the risk that (potentially high-impact) publications are assigned to the group of uncited articles solely because they are so recent (e.g., published in December 2020).

The models for uncited articles are shown in Table 4, those for articles in the top 10% of RCR in Table 5, and those for the top 1% in Table 6. In each table, columns A through C show the results for the total sample and columns D to F those for the reduced sample. Each cell in columns A through F shows the coefficient, standard error and significance level of an individual regression. For example, cell "A1" in Table 5 reports the result of regressing the FGK readability score on the dummy variable for articles not being cited at all. The coefficients on the controls and the constant term are not reported. $\overline{R^2}$ refers to the mean variance explained (McFadden's R^2) across the three models for each research field; N is the maximum sample size. The actual number of observations varies slightly across the three models due to fixed effects. If, for example, all publications in a given year are uncited, they are excluded from the analysis, as this particular subpanel provides no information on how a change in the predictor variable is associated with a change in the outcome variable. This often applies to years with very few publications—which correspondingly slightly reduces the number of observations in the regressions, as respective dummy variables all have the same value.

In Table 4, the coefficients are always negative and, for the full sample, significant at some level. The results are robust as they hold across all three readability models and both samples. For the limited sample, the explanatory power is lower and the results are inconclusive (they fail to be significant across all three readability measures) for three of the smallest four discourses. The results clearly indicate that higher readability scores reduce the probability that a publication is not cited. The significance of the effects seems to increase with the sample size, yet the results are still mostly significant for smaller samples and the reduced time period.

Table 3. Correlation between readability and relative citation ratios per technology discourse. The table shows Pearson correlations and nominal *p*-values for the twelve technology discourses and subsamples based on (relative) citation count. For the number of observations, see Table 1.

	FKG				SMOG				ARI			
	RCR	Uncited articles	10% RCR	1% RCR	RCR	Uncited articles	10% RCR	1% RCR	RCR	Uncited articles	10% RCR	1% RCR
Artificial intelligence	0.019***	0.009	0.024***	0.033***	0.021***	0.006	0.026***	0.028***	0.032***	0.008	0.039***	0.038***
	(0.001)	(0.108)	(0.000)	(0.000)	(0.000)	(0.318)	(0.000)	(0.000)	(0.000)	(0.186)	(0.000)	(0.000)
Big data	0.018***	-0.007	0.015**	-0.006	0.012**	-0.010	0.023***	-0.003	0.012*	-0.013**	0.020***	-0.005
	(0.001)	(0.242)	(0.018)	(0.315)	(0.045)	(0.090)	(0.000)	(0.624)	(0.056)	(0.033)	(0.000)	(0.378)
Robotics	0.055***	0.006	0.050***	0.028***	0.059***	0.010	0.058***	0.033***	0.075***	0.001	0.071***	0.036***
	(0.000)	(0.340)	(0.000)	(0.000)	(0.000)	(0.097)	(0.000)	(0.000)	(0.000)	(0.088)	(0.000)	(0.000)
Internet of Things	0.015**	-0.002	0.019***	0.001	0.028***	-0.013	0.036***	0.007	0.025***	-0.005	0.029***	0.005
	(0.025)	(0.722)	(0.004)	(0.841)	(0.000)	(0.058)	(0.000)	(0.302)	(0.000)	(0.504)	(0.000)	(0.467)
Virtual reality	0.002	0.031***	0.002	0.010	0.010	0.034***	0.008	0.016	0.023***	0.017**	0.019***	0.016**
	(0.761)	(0.000)	(0.732)	(0.146)	(0.156)	(0.000)	(0.280)	(0.026)	(0.001)	(0.018)	(0.006)	(0.020)
Cloud computing	0.004	0.003	0.002	0.001	0.023***	-0.0126*	0.021***	0.006	0.008	-0.004	0.005	0.002
	(0.551)	(0.701)	(0.745)	(0.962)	(0.002)	(0.087)	(0.005)	(0.404)	(0.261)	(0.546)	(0.470)	(0.842)
Blockchain	0.032**	-0.039**	0.021***	-0.006	0.030*	-0.030*	0.019	0.007	0.024	-0.021	0.011	-0.009
	(0.042)	(0.014)	(0.003)	(0.708)	(0.053)	(0.054)	(0.223)	(0.063)	(0.135)	(0.183)	(0.483)	(0.562)
Edge computing	-0.011	-0.011	0.005	-0.002	-0.005	-0.010	0.017	0.005	-0.010	-0.018	0.009	-0.006
	(0.542)	(0.536)	(0.734)	(0.916)	(0.772)	(0.572)	(0.572)	(0.788)	(0.555)	(0.303)	(0.594)	(0.740)
Autonomous driving	-0.026	0.000	-0.017	-0.022	-0.021	-0.010	-0.022	-0.015	-0.014	-0.004	-0.002	-0.004
	(0.302)	(0.990)	(0.493)	(0.384)	(0.415)	(0.397)	(0.709)	(0.552)	(0.570)	(0.880)	(0.930)	(0.870)
WBAN	0.020	-0.037	0.024	0.003	0.040	-0.041	0.050*	-0.006	0.025	-0.027	0.033	0.002
	(0.435)	(0.148)	(0.352)	(0.920)	(0.117)	(0.108)	(0.060)	(0.801)	(0.321)	(0.281)	(0.196)	(0.946)
Smart contracts	-0.025	0.062**	0.011	-0.002	-0.029	0.055*	0.003	-0.015	-0.014	0.045	0.017	0.006
	(0.432)	(0.049)	(0.723)	(0.949)	(0.365)	(0.081)	(0.914)	(0.632)	(0.665)	(0.153)	(0.581)	(0.849)
Digital twin	0.041	-0.075**	0.032	0.011	0.045	-0.069*	0.024	0.018	0.043	-0.065*	0.030	0.006
	(0.278)	(0.045)	(0.394)	(0.770)	(0.236)	(0.065)	(0.532)	(0.625)	(0.257)	(0.085)	(0.432)	(0.881)

*, **, *** indicates a difference between the full sample and the respective subsample that is significant at the 10%, 5%, or 1% level.

Table 4. Logistic regression results for uncited articles. The regressions predict articles receiving zero citations depending on the three readability measures. $\overline{R^2}$ is the average variance explained (McFadden's R^2) across each set of three models that use the same data basis. All models control for year of publication. Controls and constant term are not reported.

	All articles					Articles published before 2020				
	(A) FKG	(B) SMOG	(C) ARI			(D) FKG	(E) SMOG	(F) ARI		
	Coef. (SE)	Coef. (SE)	Coef. (SE)	$\overline{R^2}$	N	Coef. (SE)	Coef. (SE)	Coef. (SE)	$\overline{R^2}$	N
(1) Artificial intelligence	-0.016***	-0.0225***	-0.0153***	0.136	30,473	-0.0152**	-0.0217***	-0.0102**	0.024	22,705
	(0.005)	(0.0066)	(0.0039)			(0.0055)	(0.0082)	(0.0048)		
(2) Big data	-0.0197***	-0.0372***	-0.0244***	0.146	26,615	-0.0263***	-0.0490***	-0.0322***	0.034	20,212
	(0.0054)	(0.0073)	(0.0045)			(0.0069)	(0.0094)	(0.0058)		
(3) Robotics	-0.0102*	-0.0335***	-0.0222***	0.158	25,970	-0.0146***	-0.0269***	-0.0156***	0.024	22,758
	(0.0060)	(0.0089)	(0.0053)			(0.0064)	(0.0103)	(0.0058)		
(4) Internet of Things	-0.0107*	-0.0356***	-0.0139**	0.167	21,799	-0.0261***	-0.0396***	-0.0139*	0.028	15,024
	(0.0057)	(0.0088)	(0.0054)			(0.0092)	(0.0124)	(0.0076)		
(5) Virtual reality	-0.0166***	-0.0165*	-0.0107**	0.162	20.286	-0.0165***	0.0184**	-0.0125**	0.023	17,474
	(0.0054)	(0.0099)	(0.0051)			(0.0058)	(0.0089)	(0.0057)		
(6) Cloud computing	-0.0114*	-0.0389***	-0.0091*	0.115	18,344	-0.00125*	-0.0472***	-0.0102*	0.016	15,229
	(0.0066)	(0.0097)	(0.0053)			(0.0073)	(0.0114)	(0.060)		
(7) Blockchain	-0.0371***	-0.0348**	-0.0196*	0.105	4,059	-0.0721***	-0.0892***	-0.0415***	0.020	1,947
	(0.0126)	(0.0169)	(0.0104)			(0.0192)	(0.0272)	(0.0157)		
(8) Edge computing	-0.0313*	-0.0417*	-0.0253*	0.225	3,399	-0.0794**	-0.0991**	-0.0610**	0.039	1,696
	(0.0181)	(0.0228)	(0.0146)			(0.0383)	(0.0481)	(0.0311)		
(9) Autonomous driving	-0.0198**	-0.0369*	-0.0371*	0.201	1,553	-0.0244	-0.0721	-0.0470	0.064	963
	(0.0072)	(0.0201)	(0.224)			(0.0415)	(0.0539)	(0.0349)		
(10) WBAN	-0.0595*	-0.1081***	-0.0391*	0.150	1,553	-0.0621	-0.1123**	-0.0312	0.070	1,327
	(0.0305)	(0.0404)	(0.0234)			(0.0356)	(0.0477)	(0.0272)		
(11) Smart contracts	-0.0656**	-0.0629*	-0.0378*	0.113	1,006	-0.1196***	-0.0961	-0.0701*	0.018	470
	(0.0278)	(0.0353)	(0.0227)			(0.0411)	(0.0599)	(0.0374)		
(12) Digital twin	-0.077**	-0.0855**	-0.0561**	0.062	711	-0.174***	-0.1665**	-0.1349***	0.027	281
	(0.031)	(0.0389)	(0.0242)			(0.062)	(0.0744)	(0.0484)		

*,**,*** indicate significance at the 10%, 5%, 1% level.

Table 5. Logistic regression results for articles being located in the top 10% based on relative citation ratio. The regressions predict articles being located in the top 10% based on relative citation ratio depending on the three readability measures. $\overline{R^2}$ is the average variance explained (McFadden's R^2) across each set of three models that use the same data basis. All models control for year of publication. Controls and constant term are not reported.

	All articles					Articles published before 2020				
	(A) FKG	(B) SMOG	(C) ARI			(D) FKG	(E) SMOG	(F) ARI		
	Coef. (SE)	Coef. (SE)	Coef. (SE)	$\overline{R^2}$	N	Coef. (SE)	Coef. (SE)	Coef. (SE)	$\overline{R^2}$	N
(1) Artificial intelligence	0.0221***	0.0367***	0.0269***	0.006	30,473	0.0192***	0.0339***	0.0229***	0.004	22,705
	(0.0055)	(0.0088)	(0.0043)			(0.0061)	(0.0101)	(0.0047)		
(2) Big data	0.0147**	0.0323***	0.0168***	0.003	26,615	0.0135**	0.0273**	0.0139**	0.002	20,212
	(0.0068)	(0.0094)	(0.0055)			(0.0072)	(0.0109)	(0.0063)		
(3) Robotics	0.0361***	0.0878***	0.0391***	0.010	25,970	0.0339***	0.0829***	0.0317***	0.008	22,758
	(0.0049)	(0.0098)	(0.0041)			(0.0050)	(0.0104)	(0.0042)		
(4) Internet of Things	0.0244***	0.0592***	0.0286***	0.003	21,799	0.0283***	0.0697***	0.0322***	0.003	15,024
	(0.0086)	(0.0114)	(0.0068)			(0.0099)	(0.0134)	(0.0079)		
(5) Virtual reality	0.0023	0.0137	0.0131***	0.002	20.286	-0.0018	0.0032	0.0109**	0.002	17,474
	(0.0068)	(0.0116)	(0.0047)			(0.0074)	(0.0124)	(0.0049)		
(6) Cloud computing	0.0223***	0.0353***	0.0243***	0.002	18,344	0.0040	0.0426***	0.0056	0.001	15,229
	(0.0079)	(0.0123)	(0.0062)			(0.0082)	(0.0133)	(0.0065)		
(7) Blockchain	-0.0243	-0.0303	-0.0114	0.001	4,059	-0.0178	-0.0176	-0.0100	0.001	1,947
	(0.0194)	(0.0253)	(0.0158)			(0.0265)	(0.0352)	(0.0211)		
(8) Edge computing	0.0091	0.03227	0.0109	0.003	3,399	0.0411	0.0833**	0.0339	0.002	1,696
	(0.0240)	(0.0305)	(0.0194)			(0.0324)	(0.0417)	(0.0260)		
(9) Autonomous driving	-0.0213	-0.0376	0.0051	0.010	1,553	0.0183	0.0006	0.0295	0.008	963
	(0.0405)	(0.0510)	(0.0329)			(0.0483)	(0.0611)	(0.0390)		
(10) WBAN	0.0198	0.0845*	0.0220	0.006	1,553	0.0065	0.0650	0.0126	0.006	1,327
	(0.0253)	(0.0461)	(0.0195)			(0.0280)	(0.0488)	(0.0210)		
(11) Smart contracts	0.0163	0.0092	0.0192	0.007	1,006	0.0437	0.0526	0.0386	0.003	470
	(0.0398)	(0.0515)	(0.0327)			(0.0545)	(0.0732)	(0.0454)		
(12) Digital twin	0.0389	0.0381	0.0294	0.004	711	0.0769	0.0939	0.0632	0.009	281
	(0.0441)	(0.0577)	(0.0348)			(0.0710)	(0.0917)	(0.0555)		

*,**,*** indicate significance at the 10%, 5%, 1% level.

Table 6. Logistic regression results for articles being located in the top 1% based on relative citation ratio. The regressions predict articles being located in the top 1% based on relative citation ratio depending on the three readability measures. $\overline{R^2}$ is the average variance explained (McFadden's R^2) across each set of three models that use the same data basis. All models control for year of publication. Controls and constant term are not reported.

	All articles					Articles published before 2020				
	(A) FKG	(B) SMOG	(C) ARI			(D) FKG	(E) SMOG	(F) ARI		
	Coef. (SE)	Coef. (SE)	Coef. (SE)	$\overline{R^2}$	N	Coef. (SE)	Coef. (SE)	Coef. (SE)	$\overline{R^2}$	N
(1) Artificial intelligence	0.0565***	0.1215***	0.0486***	0.015	30,473	0.0507***	0.1070***	0.0426***	0.015	22,705
	(0.0104)	(0.0244)	(0.0081)			(0.0113)	(0.0284)	(0.0088)		
(2) Big data	-0.0244	-0.0178	-0.0186	0.009	26,615	-0.0117	-0.0003	-0.0047	0.004	20,212
	(0.0223)	(0.0294)	(0.0182)			(0.0247)	(0.0332)	(0.0199)		
(3) Robotics	0.0375***	0.1450***	0.0337***	0.012	25,970	0.0322***	0.1189***	0.0303***	0.011	22,758
	(0.0091)	(0.0275)	(0.0066)			(0.0102)	(0.0298)	(0.0071)		
(4) Internet of Things	0.0028	0.0320	0.0125	0.010	21,799	0.0098	0.0469	0.0247	0.004	15,024
	(0.0259)	(0.0340)	(0.0202)			(0.0301)	(0.0402)	(0.0225)		
(5) Virtual reality	0.0178**	0.0737**	0.0195**	0.013	20.286	0.0131	0.0581	0.0161	0.014	17,474
	(0.0092)	(0.0342)	(0.0094)			(0.0160)	(0.0361)	(0.0104)		
(6) Cloud computing	-0.0004	0.0272	0.0031	0.009	18,344	0.0086	0.0651*	0.0106	0.011	15,229
	(0.0250)	(0.0367)	(0.0195)			(0.0225)	(0.0388)	(0.0169)		
(7) Blockchain	-0.0210	-0.0349	-0.0276	0.017	4,059	-0.0570	-0.0267	-0.0425	0.016	1,947
	(0.0594)	(0.0781)	(0.0506)			(0.0875)	(0.1107)	(0.0722)		
(8) Edge computing	-0.0138	0.0178	-0.0230	0.022	3,399	-0.0955	-0.0143	-0.0497	0.013	1,696
	(0.0773)	(0.0957)	(0.0632)			(0.1103)	(0.1329)	(0.0886)		
(9) Autonomous driving	-0.1131	-0.0970	-0.0264	0.032	1,553	-0.0100	-0.0122	0.0357	0.041	963
	(0.1257)	(0.1535)	(0.0991)			(0.1559)	(0.1943)	(0.1211)		
(10) WBAN	-0.0073	-0.0368	-0.0070	0.022	1,553	-0.0228	-0.1004	-0.0151	0.030	1,327
	(0.0741)	(0.1457)	(0.0603)			(0.0875)	(0.1522)	(0.0676)		
(11) Smart contracts	-0.0092	-0.0826	0.0181	0.027	1,006	-0.0322	-0.0469	0.0166	0.001	470
	(0.1242)	(0.0164)	(0.0986)			(0.1899)	(0.2495)	(0.1476)		
(12) Digital twin	0.0565***	0.0955	0.0251	0.008	711	-0.0770	-0.1932	-0.1101	0.034	281
	(0.0104)	(0.1689)	(0.1082)			(0.2979)	(0.3637)	(0.2339)		

*,**,*** indicate significance at the 10%, 5%, 1% level.

Table 5 shows a split picture. For the four largest discourses—AI, big data, robotics, and IoT—we find highly significant positive effects for all readability measures in both samples on publications being in the top 10% based on RCR. This also holds for cloud computing in four of the six models. No robust (i.e. cross-readability, cross-sample) significant effects are found for any of the other samples. Accordingly, it can be concluded that readability is a significant driver of high scientific impact.

Regarding the readability of abstracts of the greatest scientific impact, only AI and robotics show significant, robust positive effects (cf. Table 6). These are the oldest samples (first mention in 1985) with comparatively many publications.

4 Discussion

Based on a large set of publications on twelve emerging technologies of different levels of maturity, this study investigated how the readability of the abstracts changes over time and how it relates to—and potentially affects—scientific impact in the form of the articles' citation counts. Three standard measures of text readability were employed.

In all of the twelve research fields, the abstracts are quite complex on average. The readability scores increased in almost all samples, meaning that the abstracts have become more difficult to understand. This result is consistent with prior research on the readability of scientific publications on marketing and tourism (Bauerly et al., 2006; Dolnicar and Chapple, 2015). Our results thus suggest that scientific discourses on emerging technologies, like academic research in general (Plavén-Sigray et al., 2017), do not become easier to understand as they mature.

A key finding with far-reaching implications, which applies to almost all of the research fields considered, is that articles with more complex abstracts have a lower likelihood of remaining uncited. This result is in line with Dowling et al. (2018)'s findings on the impact of readability on articles published in *Economics Letters*. These effects suggest that scientists have an incentive to inflate the complexity of their abstracts to maximize the number of citations, or at least to avoid not being cited. Besides authors, this result is also relevant for the strategic orientation of academic journals. Citation-based metrics such as the *Impact Factor* or *CiteScore* are a key factor in assessing the quality of journals. Academic outlets may therefore want to assess, among other metrics, the readability of abstracts when processing submissions to gauge the potential impact of an article and how it may affect journal rankings.

Along with the title and author name(s), the abstract is likely to be the first piece of information about an article that a reader sees. Due to their limited capacity to process information, people are strongly influenced by the first information they receive on a topic. This *first impression bias* means that our initial impression affects how we judge subsequent content. If the following information is inconsistent, people tend to interpret it in such a way that it corresponds to the first impression (in line with the confirmation bias (Nickerson, 1998)). Only in the face of persistent anomalies do people begin to question their first impression (Asch, 1946). Furthermore, people tend to better remember the information they received first, which is called the *primary effect* (Jones and Goethals, 1987). These effects underline the relevance of the abstract and its readability.

In line with the *Doctor Fox Phenomenon*, which states that academic prestige correlates with complexity in communication (Armstrong, 1980; Naftulin et al., 1973), academics could signal their (purported) research competence though complex writing, which in turn result in higher citation counts. Thus, authors would have an incentive to make their abstracts as complex as possible to improve their chances of achieving scientific impact. If higher readability scores signal competence, there is also an incentive to increase or control an abstract's linguistic complexity over the various rounds of the scientific peer review process in order to feign equal or higher quality.

4.1 Limitations

The first limitation concerns the source of the data. They are obtained from published papers contained in the WoS database, all of which satisfy certain quality requirement—the WoS only indexes selected journals, books and conference proceedings. Our data source may therefore entail a selection bias in terms of quality and/or readability—similarly to the potential downward bias mentioned by McCannon (2019). Future research could additionally include "less prominent" literature, possibly building on Google Scholar. Another potential source of selection bias consists in our choice of research fields, whose subjectivity was already discussed above. We specifically selected a larger number of subject areas to minimize any such bias.

Secondly, in the multivariate analysis, the fact that some models explain only a small share of the variance indicates that there are important drivers of citation counts besides readability. Integrating further control variables could improve the explanatory power of the models, the significance of the results, and thus the soundness of the conclusions.

The use of readability formulas is associated with certain disadvantages and limitations, which can of course affect the analyses and implications presented. Readability formulas do not allow any real judgment about how comprehensible the meaning of a text really is. They do not provide any indication of prior knowledge required or coherence of a text and cannot judge mood or tone (Redish, 2000). The wide variation of readability measures is the reason that several measures were examined in this study for the purpose of robustness. However, it should be noted that text analysis is constantly evolving and the metrics used here are not necessarily the "best" ones and, depending on the context and goal, other metrics based on, e.g., word phrases (De Clercq et al., 2014) or semantics (Crossley et al., 2017), may be more appropriate to assess a text (Crossley et al., 2019).

4.2 Future research

The relationship between abstract readability and scientific impact could be determined with greater precision if a follow-up study were to also incorporate data on the "actual quality" of the articles. Any such an assessment of quality would, for a data set of this size, of course have to rely on proxies, with all the associated limitations. Additionally, it should be investigated whether there is a quadratic effect. It is conceivable that overly complicated abstracts may even harm citations, or that the effect is not linear, but that the marginal impact eventually decreases.

The effect of less complex abstracts being more likely to remain uncited may result from a citation bias against non-English-native-speaker authors. Such people write less complicated sentences, and the reader may think that the content is then also less citation-worthy. This is a significant question for future research.

Given that scientific articles change over the course of the publication process (e.g. following peer-review) and the publication of working papers is increasingly becoming common practice, it would be possible to investigate how the readability of abstracts changes in the different stages of publication. This would allow us to identify how a gradual change in readability corresponds to specific goal, such as citation counts. The results may help authors and journals develop better publication strategies. The study by Marino Fages (2020) can provide a basis for such an investigation.

For a complex abstract to be a credible signal of article quality, it must be costly (to fake). But what exactly is the cost? Future research might ask subjects with and without detailed knowledge of readability metrics to purposely increase the readability scores without changing the contents of the texts. The time it takes them to achieve a given increase in the readability scores may be regarded as a measure of cost. It remains open whether the chances of citations would increase at all in the context of differently complex language with the same content or same quality. To test this, one could give scientists in an experiment some abstracts to read, which have the same content and include either easy and complex language. The variants are randomly distributed among the scientists. These individuals are then asked to determine the presumed content quality (citation worthiness) of the papers.

The semi-subjective selection of twelve emerging technology discourses for this study satisfies its exploratory nature. Future research could examine additional technologies, look at commonalities between discourses, or examine the title and main text of the publications in addition to the abstracts. Research on readability has already looked at scientific publications in general, at individual journals and sectors, and now at technologies. Other superordinate areas, such as countries, languages, theories or phenomena, may also be of interest.

5 Conclusion

Given their potential to transform systems, markets and processes (Martin, 1995; Rotolo et al., 2015), emerging technologies are clearly a relevant factor for policy-making, hence the great interest to identify them at an early stage and to assess, forecast and evaluate their development (e.g., Joung und Kim 2017; Kyebambe et al. 2017; Lee et al. 2018; H. Xu et al. 2021). One step to this end can be to identify which scientific publications will likely have great impact. The readability of the abstracts, i.e. the level of education that is required to understand them, can be one of many pieces of information from which to systematically classify and analyze academic discourses and their development. While text readability, scientific impact and emerging technologies have received ample attention from the scientific community, little context has been established between these three factors. It would be particularly valuable to see whether any fundamental cross-technology similarities over time can be observed.

This study has aimed to provide that bridge between readability, scientific impact and academic research on emerging technologies. To this end, twelve technological discourses of various degrees of maturity were selected. For these discourses, we collected all publications contained in the WoS database, obtaining a total of 135,502 articles. The largest and one of the oldest discourses is AI with 30,473 scientific articles published between 1985 and 2020, and the smallest is Digital Twin with 711 publications. For each publication, we calculated the readability score of the abstract using the readability measures FKG, SMOG, and ARI. In addition, normalized citations were calculated for each article.

We find that the readability scores, i.e. the complexity of the language, have increased over time in virtually all discourses. This result can be used to better understand and predict the growth and development of emerging technologies. However, a clear interpretation requires further in-depth analysis and robustness checks to clarify whether, for example, this phenomenon is specific to certain technologies or extends to all academic texts. Our analysis furthermore shows that higher readability scores significantly reduce the likelihood of articles not receiving any citations. For the larger and older discourses, higher readability scores promote the chances of an article being in the top 10% or top 1% in terms of citations. Hence the title of this paper: "Readability affects scientific impact". While we find significant relationships between readability and scientific impact, we cannot determine the extent to which citations are actually influenced by readability and the extent to which a causal relationship exists. Future research should explore the questions of causality and influence of readability on scientific impact in more detail, as this determination has high relevance for potential implications.

One implication of these results is that "the market" for scientific publications, at least on these specific technologies, may be subject to critical incentives. If readability drives scientific impact, authors have an incentive to (artificially) increase the complexity of their writing style in order to signal the quality of their papers to the readers. Authors who resist this temptation run the risk of being systematically underestimated. Any such complexity inflation would impair the ability of the readers to screen the quality of the articles, which makes the scientific system less efficient. Future research should verify whether such a moral hazard in academic (abstract) writing exists, i.e. whether authors intentionally communicate their work in an unnecessarily complex manner. Such behavior would run counter to general scientific goals, such as clarity and simplicity, and would challenge readers, academic journals, research institutions and other stakeholders to develop an appropriate response.

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Declarations

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on request.

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Not applicable.

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