Options, Futures and Other Derivatives, aptly observes[12], Black–Scholes theory is popular among traders because it has only one unobservable parameter, which is related to the volatility. This simplicity makes it appealing, but it is based on a modelling assumption about how fluctuations in the price of the asset underlying the option are distributed. At the time, this assumption seemed reasonable, but its limitations became increasingly obvious in later years.

One indication that the Black–Scholes model might be an oversimplification was that the volatility parameter implied by option prices in the market seemed to depend on the strike price of the option. Very high and very low strike prices are associated with higher volatility than are intermediate prices, and this gave rise to the term 'implied volatility smile' (Fig. 2). Volatility is also not the same for different contract durations. And varying the strike price and contract duration simultaneously results in an implied volatility surface, which has formed the focus of several decades of research in mathematical finance.

Over time, many of Black, Scholes and Merton's original modelling assumptions were deemed simplistic, and new, more complex models emerged that are better equipped to reproduce the smile. These models typically allow more-general movements of the underlying asset price than does the Black–Scholes equation. Traders can now choose to work with models that have stochastic (random) volatility, ones with 'rough' volatility or those involving jumps in asset-price movements, to name just a few.

Today, the world of finance is in a post-Black–Scholes era, in which the theory's historical importance is undisputed, but some say that the model itself can be more distortive than helpful for understanding the microstructure of markets[13]. Decades of research have gone into improving financial models; into calculating the risks connected with them; and – because all models are imperfect in some way – into understanding the implications if the models are wrong.

Considerable research now goes into teaching machines to price and hedge options in an automated way[14,15], and with more-general settings than have previously been possible[16]. Tremendous effort is also being spent on understanding how trading at extremely high frequencies affects the market[17], and how pricing strategies can be built to withstand ever-changing market environments. Finally, with the climate crisis looming, focus is shifting towards understanding and optimizing market incentives that help to protect our environment. However, although priorities have changed, it's safe to say that neither the markets nor financial research would be where they are now had it not been for Black, Scholes and Merton's extraordinary work.

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Computational social science

People, not algorithms, choose partisan news

Eni Mustafaraj

Analysis of people's web searches and visited websites suggests that it is more likely that they are choosing to engage with partisan or unreliable news than that they are being unduly exposed to it by search-engine algorithms. **See p.342**

Believing false news or conspiracy theories on the Internet has real-world consequences. For instance, a discredited conspiracy theory known as Pizzagate gave rise to the much bigger QAnon conspiracy, which ultimately contributed to the attack on the US Capitol building in January 2021 (see https://bbc.in/3zBFFcb). It's often thought that the personalized algorithms of big platforms such as Facebook and Google facilitate exposure to problematic information[1], keeping their users in 'filter bubbles' and 'echo chambers' that distort their view of reality[2]. But scientific studies that try to measure this phenomenon are rare. On page 342, Robertson *et al.*[3] describe their attempt to quantify both exposure to and engagement with online news. They show that a person's choices trump Google Search's algorithmic recommendations in terms of their consumption of unreliable or partisan news.

Healthy democracies depend on factually accurate news, so it is crucial to determine whether algorithmic curation exacerbates people's exposure to, and tendency to consume, partisan or unreliable news stories. But how can we do this scientifically? In 2015, scientists studied Facebook's news feed, and concluded that individual choice was more effective at limiting exposure to ideologically diverse news than was algorithmic filtering[4]. However, this study was conducted by researchers at Facebook, and the data that would allow its replication were not available to scientists employed elsewhere.

This situation is the norm for research involving online platforms. When *The New York Times* revealed in 2006 how easy it was to identify individuals from their search history in an anonymized data set shared by the company AOL (see https://nyti.ms/2USiiDM), online platforms took note, and sharing data with external researchers became a rarity. To circumvent this type of data-access issue, some have called for online information spaces to be studied in the same way as one might study pollution – in an 'ecological' framework that analyses the interactions of individuals with online applications in their natural environments[5].

Robertson *et al.* have done just that. Similar to the way in which environmental scientists install sensors around the globe to collect ecological data about weather conditions and pollution, the authors asked survey participants – US citizens recruited through a third party – to install an extension on their browser that allowed the researchers to gather information about three types of data: Google Search results pages, links followed from those pages and all other URLs visited while browsing.

The authors collected these data in two waves. In the first wave, in 2018, they collected

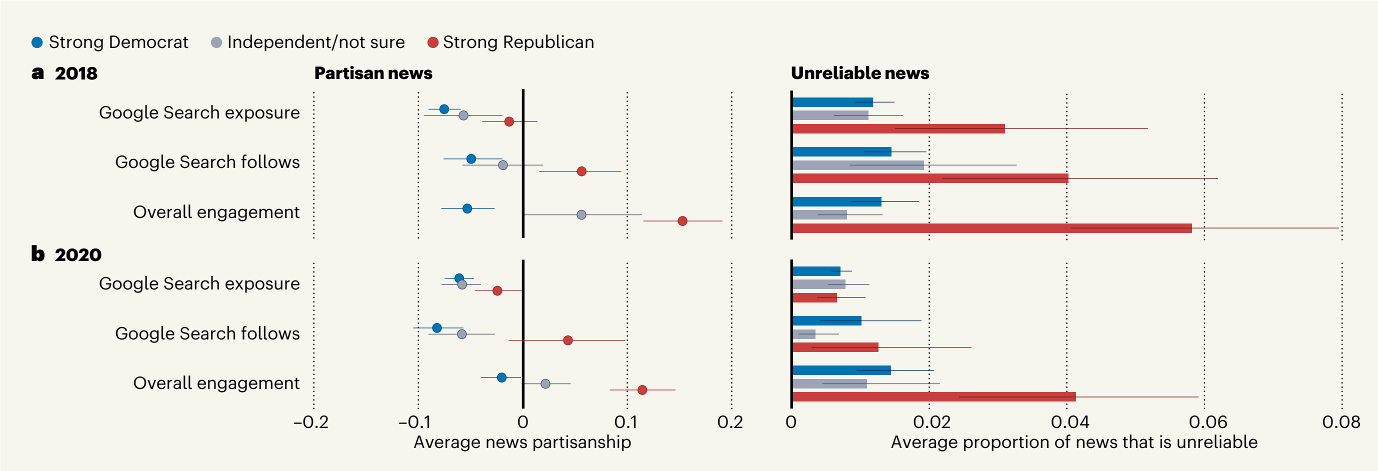

Figure 1 | How political beliefs affect web browsing. Robertson *et al.*[3] analysed the Google searches and online news consumption of people in the United States who identified as strongly Democrat, strongly Republican or Independent, in the months preceding the US elections in 2018 and 2020. They investigated the participants' interactions with partisan news sites and unreliable news sites, classed in three ways: exposure (seeing a website in a search-results page), follows (link clicks from the search page) and engagement (all web-page visits). The authors rated each news outlet visited using a partisanship score, with numbers further away from 0 being more partisan, and as either reliable or unreliable. There was no significant difference between the groups' exposure to unreliable news or how partisan that news was, but there were significant differences in engagement, with strong Republicans being more likely to engage with such news. (Figure adapted from Fig. 2 of ref. 3.)

three months' worth of data from around 300 participants, with oversampling of those who were strongly politically partisan. For the second wave, in 2020, they collected data from roughly 600 participants across the political spectrum over nine months. They chose these two time periods because they preceded US elections in 2018 and 2020 – events that typically lead to more news consumption (see https://bit.ly/3jTbPur).

The researchers define exposure as the links that users see in Google Search result pages – the combined data set includes about 330,000 such pages. Engagement consists of visits to websites that were not found from the search and clicks from links included in the search-result pages (a subset of engagement dubbed follows). Almost 46 million URLs were collected in this way. Not all visited websites were relevant to the study, so Robertson and colleagues focused only on URLs that belonged to news outlets identified by previous research. They labelled each of these outlets as either reliable or unreliable, on the basis of information from two independent sources, and gave them a partisanship score established in their previous work[6].

Robertson *et al.* grouped participants according to their political self-identification along a seven-point scale, ranging from strong Democrat to strong Republican. They then calculated, on average, how much partisan news and how much unreliable news each group was exposed to, followed and engaged with.

The comparison of the three most politically salient groups of participants (strong Democrat, Independent and strong Republican) revealed only slight differences in exposure to partisan news (Fig. 1). In other words, the filter-bubble effect was not evident – Google Search does not seem to show its users news that matches their political identity.

The group differences were more noticeable for 'follows', and became significant between all groups when comparing engagement. This means that there is evidence for the echo-chamber effect, in which participants choose news that matches their political identity.

In line with a 2018 qualitative study[7], some of the observed differences between the groups were driven by search-query formulation – an initial search query such as 'taxes are bad' or 'taxes are good' will produce results that support those partisan claims.

"There is evidence for the echo-chamber effect, in which participants choose news that matches their political identity."

Moreover, the authors found that, in 2020, 11.9% of participants accounted for 90% of the engagement with unreliable news, and that there was proportionally less unreliable news in the search results from 2020 compared with 2018. Participants who identified as strong Republicans were the most likely to engage with partisan and unreliable news – a result corroborated by related research (see https://politi.co/3Xn2VnF).

Robertson and colleagues' work is an important step towards establishing valid data-collection practices for studying exposure to and engagement with online news. By demonstrating that people's own actions are more influential to their information diets than is a platform's algorithmic curation, the group provides a strong argument for increasing and diversifying efforts for online-information literacy. In 2021, the US National Science Foundation awarded US$9 million to 12 groups to research trust and authenticity in communication systems (see https://bit.ly/3WZMmhI), recognizing it as a 'complex societal challenge'. It is a valuable investment, but more public funding and institutional support, including public-safeguarding policies (similar to those set by the US Food and Drug Administration), are needed to achieve a lasting impact.

Some of the study's limitations are invitations to continue this line of research. These include the focus on Google Search (which is justifiable, given Google's dominance in online search); collection of data on desktop-only devices (it is technically more challenging to collect mobile-phone browsing data); and reliance on metrics for partisanship or reliability at news-outlet level, rather than news-story level. Most importantly, changes in our online information environment increase the urgency for both more research of this kind and sustained efforts to improve online-information literacy. These changes include the fast rise in the popularity of TikTok and its adoption as a search engine by younger audiences (see https://nyti.ms/3XeXCGw) and the emergence of powerful language models such as ChatGPT that can generate believable falsehoods at scale (see https://bit.ly/3ZoqONl).

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Materials science

Failure of solid-state batteries probed

Kelsey B. Hatzell & Maha Yusuf

The development of a promising type of battery has been plagued by an issue that causes these devices to fail — lithium filaments grow in the electrolyte. An investigation of this failure mechanism could help to solve the problem. **See p.287**

Rechargeable lithium-ion batteries are crucial in a range of applications, including portable electronics, electric vehicles and grid-scale energy storage. Such batteries depend on the movement of lithium ions between an anode and a cathode through a liquid electrolyte. A promising strategy for the next generation of rechargeable batteries is the use of solid electrolytes and an anode made of lithium metal — such cells are known as lithium-metal solid-state batteries. However, these devices are prone to a failure mechanism in which filaments of lithium, known as dendrites, form during battery operation and pierce the electrolyte. On page 287, Ning *et al.*[1] cast light on this mechanism, revealing details that might bring practically useful lithium-metal solid-state batteries closer to reality.

Lithium-ion batteries have many potential uses because they are modular, portable and reliable. They also benefit from long lifetimes, high energy density (which prolongs use before recharging is required) and high power density (which correlates with short charging times). Nevertheless, there is still a continuous push to improve the safety, energy density and power density of these batteries.

In conventional lithium-ion batteries, the liquid electrolyte is flammable and can drive unwanted side reactions that limit the battery's lifetime. Solid-state batteries, which instead use a solid electrolyte, are being intensively researched by academic, industrial and government researchers[2], in part because of claims that such batteries are safer than their conventional counterparts[3]. Solid-state batteries that have a 'bipolar stacking' configuration and energy-dense anodes might also offer notable improvements in energy density and power density[2].

Lithium metal has many properties that make it a potentially good material for anodes in solid-state batteries. For example, it has a low density (0.534 grams per cubic centimetre), low electrode potential (−3.040 volts compared with a standard hydrogen electrode; this is beneficial for making high-voltage batteries) and high energy density (3.86 amp hours per gram). Despite this promise, and more than 40 years of research, major challenges remain that have prevented lithium metal from being adopted as an anode material in rechargeable solid-state batteries.

One vexing issue is the formation of lithium-metal dendrites. In conventional batteries containing liquid electrolytes, this problem is often ascribed to the formation of gradients in the concentration of lithium ions in the electrolyte. This can drive local charge instabilities at interfaces with electrodes, causing dendrites to grow[4]. Concentration gradients cannot form in solid electrolytes, and so this ought to solve the problem — yet solid electrolytes in batteries are still pierced by dendrites, leading to short circuiting.

Ning *et al.* now explore the underlying mechanisms of dendrite initiation and propagation in lithium-metal solid-state batteries. Maintaining contact between the solid electrolyte and lithium metal is essential for achieving reversible and uniform lithium stripping (removal of lithium from the anode during discharge) and deposition (addition of lithium to the anode during charge), both of which are necessary for successful battery operation. Unfortunately, the contact area between the anode and electrolyte can decrease when lithium metal is oxidized during discharging to produce electrons and lithium ions, a process called electrodissolution. This can leave voids in the lithium metal that accelerate battery failure. Void formation can often be counteracted by the application of pressure, but this does not solve the problem completely and can cause anode degradation through various mechanisms[5].

In their study, Ning *et al.* examine the

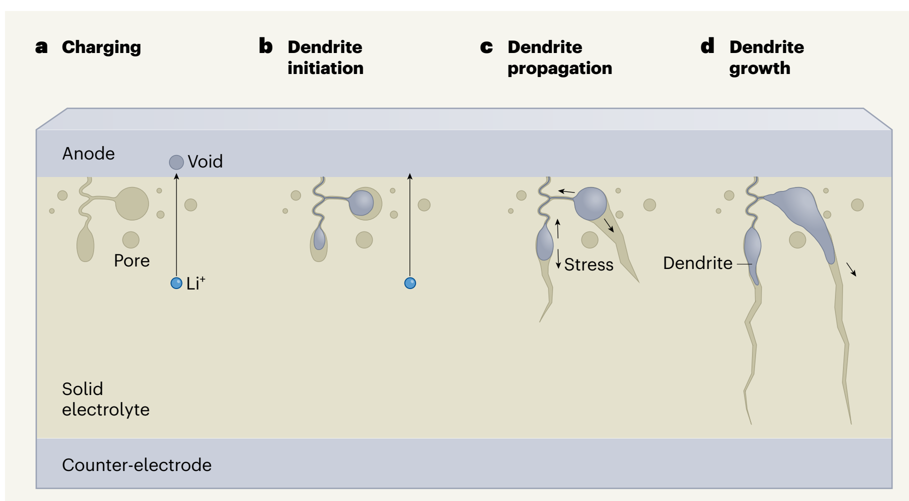

Figure 1 | Exploration of the initiation and propagation of lithium dendrites in batteries. Ning *et al.*[1] studied failure mechanisms that occur at the anode in lithium-metal solid-state batteries. Failure involves the formation of lithium filaments (dendrites) that pierce the battery's ion-conducting electrolyte. In the authors' experiments, a solid electrolyte is sandwiched between a lithium anode and a lithium counter-electrode. **a**, During charging, lithium ions (Li^+) move through the electrolyte towards the anode, where they combine with electrons to form lithium metal that is deposited on the anode. **b**, The lithium fills any voids in the anode and grows through tiny cracks in the electrolyte, filling any pores. **c**, Further charging deposits more lithium in the pores, generating stress that wedges open bigger cracks. **d**, Multiple charging and discharging cycles result in the growth of a dendrite and cracking that eventually cause catastrophic failure of the electrolyte.