The Decline in the Transmission of Scientific Ideas[*]

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Abstract

We document that the diffusion of new scientific ideas beyond their field of origin has declined substantially over the past four decades. This contraction is closely linked to increasing specialization in scientific language: research that employs more technical terminology tends to be adopted less broadly. We develop a theory of scientific discovery in which the diffusion of new ideas depends on the degree to which potential adopters can understand and process them. When introducing their discoveries, scientists face a tradeoff between technical communication targeted at their immediate peers and more accessible language meant to reach broader audiences. As knowledge accumulates and research at the frontier builds on deeper layers of prior work, this tradeoff increasingly favors specialized language, limiting diffusion. Policy interventions that align scientists' incentives can broaden adoption and increase the social value of scientific research.

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1 Introduction

Many influential scientific discoveries generated their largest benefits by finding applications outside the boundaries of their original field. X-ray crystallography, developed in physics to study the atomic structure of crystals, became a central tool in molecular biology and made it possible to infer the double-helix structure of DNA. The fast Fourier transform, introduced as a computational tool in electrical engineering, revolutionized medical diagnostics by enabling magnetic resonance imaging. More recently, CRISPR, first identified as part of basic research in bacterial immune systems, has become a widely used tool for targeted genetic editing in many areas of biology, medicine, and agriculture.

Yet the reach of new scientific ideas has been narrowing. Using the full corpus of publications indexed in PubMed, we identify newly introduced scientific concepts and measure their breadth of diffusion as the semantic distance between the papers that introduce a concept and those that subsequently adopt it. This measure has declined substantially over the past four decades: concepts introduced in 2009 diffused roughly half a standard deviation less broadly than those introduced in 1980. This is not an artifact of science becoming more homogeneous over time—if anything, by our measure, scientific articles have grown modestly more dispersed—but reflects a genuine contraction in how far new ideas diffuse from the field where they originate.

This contraction speaks directly to a central question in the economics of innovation: Why do the returns to research appear to be falling? A growing literature documents that science has become less productive, in the sense that sustaining a given rate of advance requires ever-larger investments in research (Jones, 2009; Bloom et al., 2020; Park et al., 2023; Ekerdt and Wu, 2024; Fort et al., 2025). A narrowing of diffusion points to a distinct but complementary force: even if the rate of scientific discovery remains unchanged, the value society realizes from new ideas may decline if their diffusion is limited to a narrower set of fields.

In this paper, we study the diffusion of science starting from a simple premise: the breadth of adoption of new ideas depends on how intelligible they are to audiences outside their originating field. We develop a theory of scientific discovery in which *comprehension*—the extent to which potential adopters can understand and process a new idea in a way that enables application—depends on both the depth of the accumulated knowledge behind the idea and the accessibility of the language used to introduce it. As the stock of knowledge grows and new ideas build on deeper layers of prior work, scientists optimally favor more specialized language, and diffusion narrows.

We bring this mechanism to data on biomedical publications indexed in PubMed and find evidence for its central implications.

That scientists make deliberate choices about how to communicate their research, and that these choices are consequential for the impact of their work, is an observation that recurs throughout the history of science. The philosopher of science Thomas Kuhn argued that the adoption of a new paradigm requires shared frameworks that facilitate mutual understanding (Kuhn, 1962). Richard Feynman claimed that his introduction of diagrammatic methods was essential for making quantum electrodynamics usable beyond a small group of specialists, allowing physicists in other areas to apply and extend the theory.[1] By contrast, the work of Josiah Willard Gibbs on statistical mechanics was characterized by such mathematical density that even Albert Einstein famously found it "inscrutable," contributing to a long delay before the scientific community could fully integrate his insights.

Why do ideas vary so markedly in how they are communicated? Our central argument is that the breadth of an idea's diffusion reflects a communication tradeoff that scientists face when conveying their discoveries. We formalize this in a model in which new ideas have potential applications across many fields and are adopted when potential users can comprehend them well enough to apply them in their own domain. Comprehension depends on three elements: the *scientific distance* between the originating field and the potential adopter, the idea's *knowledge depth*—how far it sits from basic, self-evident principles—and the *accessibility* of the language used to communicate it.

These three elements interact and affect the comprehension of an idea in intuitive ways. Comprehension declines with scientific distance, as ideas become harder to understand when the cognitive frameworks of potential adopters differ from that of the originating field. This decline is steeper for ideas with greater knowledge depth, because such ideas rely more heavily on the assumptions, methods, and accumulated knowledge embedded in the originating field's cognitive framework. Scientists make deliberate communication choices that affect comprehension in two opposing ways. By using more accessible language, scientists can bridge cognitive distance and make ideas more comprehensible to distant audiences (*bridging effect*), at the cost of reduced precision and technical detail, which lowers comprehension for all audiences (*dilution effect*). On net, more accessible language increases comprehension for distant audiences but lowers it for nearby

[1] Frank Wilczek noted that key calculations underlying his Nobel Prize-winning work would have been "unthinkable without Feynman diagrams" (Frank Wilczek, "How Feynman Diagrams Almost Saved Space", Quanta Magazine, 2016, accessed January 2026).

ones. Both the benefits of bridging and the costs of dilution are amplified as the depth of knowledge underlying the idea increases.

Three implications follow. First, when the dilution effect is more sensitive to knowledge depth than the bridging effect, scientists introducing deeper ideas optimally choose less accessible language. Intuitively, the precision lost to simplification grows more costly as ideas move further from self-evident principles. Second, more accessible language broadens adoption by making ideas comprehensible to more distant fields. Third, the first two implications together imply that as the knowledge underlying new ideas deepens, their diffusion narrows. This occurs both because deeper ideas are intrinsically harder for distant fields to grasp and because, when dilution costs are sufficiently responsive, scientists choose less accessible language. A scientist's *own-field bias*—the degree to which adoption by nearby peers is valued relative to distant ones—deepens this contraction and drives a wedge between the private and social returns to diffusion.

We bring these insights to the data using a corpus of scientific publications indexed in PubMed. We identify newly introduced scientific concepts and track their adoption across fields and over time. For each concept, we construct measures that correspond to the objects formalized in the model. Knowledge depth is proxied by the degree of specialization of the authors introducing the concept.[2] Language accessibility is measured using the prevalence of common words in the abstracts of the papers that introduce the concept.[3] Breadth of diffusion is measured using semantic distances between the abstracts of the papers introducing and adopting the concept.

Tracking these objects over the past four decades, we document patterns that align closely with the theory. The knowledge depth of newly introduced concepts has increased steadily, the language used to introduce them has grown less accessible, and their breadth of adoption has narrowed. This pattern does not reflect a mechanical feature of the diffusion measure: placebo simulations holding fixed the timing and subject area of adoption show, if anything, a mild movement in the opposite direction, indicating that scientific articles have not become more semantically uniform over this period.

We then use these measures to test the model's three implications. First, concepts built on deeper knowledge are introduced using less accessible language, consistent with dilution costs rising

[2]Following Jones (2009), who argues that pushing the frontier of a deeper body of knowledge requires greater individual specialization, we treat the specialization of a concept's introducing authors as an observable proxy for its knowledge depth. Section 4 describes the construction of this measure and shows that it rises over the sample period, as highlighted by the existing literature (e.g., Wuchty et al., 2007; Jones, 2021).

[3]Common words are defined as terms that appear frequently in papers published in the previous five years, reflecting language that was widely used in the scientific literature at the time.

more steeply than the benefits of bridging. Second, more accessible concepts diffuse more broadly, even after accounting for intrinsic characteristics of the idea and its relevance to a specific field. Finally, deeper concepts diffuse less broadly, with changes in language accessibility accounting for a substantial share of this relationship.

These patterns suggest that the social value of science can decline as the stock of knowledge grows, even when the intrinsic value of new discoveries remains unchanged. To study these long-run implications, we embed the mechanism in a simple Romer-style growth model. As knowledge accumulates and new ideas build on deeper layers of prior work, scientists choose less accessible language, diffusion narrows, and knowledge growth slows endogenously. The model also highlights a role for institutions and policy. When researchers' incentives are aligned with the planner's objective, so that they do not disproportionately favor adoption by nearby fields, communication becomes more accessible, the breadth of diffusion expands, and both the realized social value of scientific discoveries and long-run growth increase.

Related Literature. This paper relates to a large literature on the social value of science and the barriers that limit its diffusion. A central idea in this literature is that scientific discoveries generate value only insofar as they are accessed, adopted, and used by others. Existing work has studied the downstream use of science in applied innovation (Ahmadpoor and Jones, 2017; Yin et al., 2021a), by firms (Cohen et al., 2002; Arora et al., 2020; Marx and Fuegi, 2020; Shvadron, 2023; Krieger et al., 2024), and in public policy (Yin et al., 2021b), along with the institutions that shape research incentives (Azoulay et al., 2019; Bryan and Williams, 2021; Clancy et al., 2023). A related literature identifies specific frictions that impede diffusion: coordination failures in general-purpose technologies (Bresnahan and Trajtenberg, 1995), limited awareness of or access to knowledge (Furman and Stern, 2011; Nagaraj et al., 2020; Berkes and Nencka, 2024), institutional boundaries that influence the publication process and discourage pivoting (Myers, 2020; Krieger et al., 2025; Hill et al., 2025), limited opportunities for interaction across researchers and fields (Catalini, 2018; Lane et al., 2021; Berkes and Gaetani, 2021), and biases in whose ideas are recognized and used (Cheng and Weinberg, 2025). Our paper contributes to this literature by emphasizing comprehension as a barrier to broad diffusion: ideas may fail to diffuse not because adopters cannot access them but because they cannot readily understand and apply them outside the field in which they originate. This relates to the notion of absorptive capacity introduced by Cohen and Levinthal (1990), whereby a firm's ability to recognize, assimilate, and use external ideas depends on its prior related knowledge. Our theory also highlights a source of inefficiency:

institutional incentives are such that scientists introducing new ideas value adoption by nearby audiences more than adoption by distant ones, so their communication choices can favor within-field recognition even when broader diffusion would generate greater social value.

A second closely related strand studies communication, language, and dissemination as drivers of the diffusion of scientific knowledge. Prior work documents a long-run decline in readability and a growing reliance on technical and field-specific language (e.g., Hayes, 1992; Plavén-Sigray et al., 2017; Barnett and Doubleday, 2020), but offers limited insight into the mechanisms driving these trends or their consequences for diffusion. More recent work examines communication barriers more directly. Mumtaz (2025) shows that translating scientific findings into more accessible language increases firms' use of academic research. Using methods from computational linguistics, Kong et al. (2023) show that patents filed by university inventors are more readable than patents filed by corporations. Consistently with this result, Wang (2025) finds that commercialization incentives introduced by the Bayh-Dole Act led university inventors to strategically reduce the readability of their patents. Our theoretical framework contributes to this emerging literature by modeling communication as a deliberate choice made by scientists in response to incentives and to features of the broader research environment. In particular, it explains why the accumulation of knowledge can make specialized language more attractive even when accessibility would broaden the reach of scientific ideas.

Finally, our results speak to work on the slowdown in research productivity, where rising investment yields progressively smaller gains in new ideas and growth (e.g., Jones, 2009; Bloom et al., 2020; Ekerdt and Wu, 2024; Fort et al., 2025). We show that knowledge accumulation can reduce the realized social value of science by narrowing the breadth of diffusion, even when the intrinsic importance of discoveries is unchanged. In this respect, our analysis complements Ganguli et al. (2026), who show that declining similarity across inventions, and the associated weakening of spillovers, accounts for a substantial share of the observed decline in research productivity. Our framework provides a micro-founded mechanism for why scientific distance becomes more constraining over time: as ideas grow more detached from basic principles, scientists optimally choose to use more specialized language, limiting the ability of researchers in other fields to understand and apply them.

Outline. The remainder of the paper is structured as follows. Section 2 presents the theoretical framework and derives its implications for communication choices and diffusion. Section 3 describes the data. Section 4 introduces the empirical measures and documents long-run trends in knowledge depth, language accessibility, and diffusion. Section 5 tests the core predictions of the model. Section 6 embeds the framework in a simple Romer-style growth model to study the long-run implications for the social value of science. Section 7 concludes.

2 Model

To guide our empirical analysis, we present a stylized model that captures key features of how new scientific ideas spread and are adopted across multiple domains.

We consider a setting in which researchers develop new scientific ideas of general-purpose nature, that is, with potential applications beyond the field where they originate. Whether a new idea is adopted in a given field depends on how effectively potential adopters from that field can recognize the value of the idea and understand its functioning, in a way that makes its application possible. We summarize this in a single metric, which we refer to as *comprehension*.[4] Three ingredients determine how well adopters from a given field comprehend an idea.

The first ingredient is *scientific distance*: as the adopting field's cognitive framework—its objectives, methods, background knowledge, and terminology—differs from that of the field of origin, the idea becomes more difficult to comprehend.

The second ingredient is the *knowledge depth* underlying the idea. Knowledge depth can be thought of as the size of the conceptual step separating it from basic, self-evident principles. It grows with the accumulated knowledge in the field of origin and with the rising complexity of new discoveries once simpler insights are exhausted. Scientific distance and knowledge depth interact with each other in an intuitive way: ideas close to basic principles are broadly comprehensible across all fields, whereas deep ideas become increasingly harder to understand as scientific distance increases.

The third ingredient depends on a deliberate choice made by researchers. When communicating their ideas, researchers choose how much technical detail, rigor, and field-specific terminology to use. We summarize this communication choice in a metric which we refer to as *language accessibility*. More accessible language bridges cognitive distance, making the idea more intelligible to external audiences (*bridging effect*). At the same time, it also creates a *dilution effect*, by

[4]Comprehension does not require complete technical mastery. It captures a functional level of understanding sufficient to recognize an idea's potential value and apply it in a new context. The required level of understanding varies with the specific characteristics of the adopter and the potential application. We model this by assuming the threshold necessary for adoption is stochastic and idiosyncratic across potential adopters.

reducing precision and technical depth, which lowers comprehension for all audiences.[5]

Researchers choose language accessibility to maximize the mass of adopters of their ideas, but weight adoption by nearby fields more heavily than adoption by distant ones (*own-field bias*).[6] Their optimal choice balances bridging against dilution, and how the tradeoff is resolved depends on the idea's knowledge depth and on the strength of the own-field bias.[7]

2.1 Setting

We formalize these ingredients in a static setting in which a researcher develops a new scientific idea with an intrinsic degree of knowledge depth $k > 0$. There is a unit mass of potential adopters of the idea, uniformly distributed over a continuum of fields indexed by $i \in [0, 1]$. Fields are ordered so that i represents both a field's label and its distance from the field of origin of the idea, which we set to $i = 0$.

Each adoption generates a constant social payoff $v > 0$. The aggregate social value of the idea, V, is therefore proportional to the total measure of adopters across fields, M:[8]

$$V = v\, M = v \int_0^1 \mu(i)\, \mathrm{d}i, \tag{1}$$

where $\mu(i)$ denotes the adoption rate in field i. The researcher and adopters also derive intrinsic value from adoption, but we assume this to be negligible from a social welfare viewpoint.

[5] Language accessibility is the only choice variable in the model. Both knowledge depth (an intrinsic property of the idea) and scientific distance (an intrinsic property of the relationship between fields) are taken as given by the researcher. The tradeoff between the bridging and dilution effects is related to the tradeoff between "brevity" and "clarity" that Autor and Thompson (2025) use—building on Barlow et al. (1961)'s Efficient Coding Hypothesis—as the basis for measuring the degree of expertise embodied in different job tasks.

[6] In other words, researchers aim at maximizing scientific recognition, but they place more weight on recognition by closer fields. Own-field bias can arise from both institutional incentives—such as promotion systems that emphasize within-field citations and peer recognition—and social and cognitive factors, as researchers naturally place greater weight on feedback from audiences they interact with regularly and whose expertise they can readily evaluate.

[7] In practice, researchers may communicate the same idea through multiple outlets, such as technical papers and more accessible forms of dissemination. While this possibility can mitigate the tradeoff we model, it does not eliminate it or alter its nature. Producing accessible communication is costly in terms of time and effort, its effectiveness declines as ideas become more complex, and incentives to engage in such dissemination depend on researchers' interest in reaching audiences outside their field. While we abstract from this channel here, we discuss its role and opportunities for future research in the Conclusions. Allowing for multiple communication channels would not overturn the model's qualitative implications for the breadth of adoption and the social value of science.

[8] While the realized value of an idea may differ across fields, we abstract from this heterogeneity and assume that, ex ante, adoption in any field has the same expected social value. This corresponds to a setting in which a social planner has no information about the field-specific potential of the idea and, as a consequence, evaluates policies based on their ability to maximize overall adoption.

2.1.1 Comprehension and adopter's decision

Each field i attains a degree of comprehension of the idea $\Gamma(i) \in [0,1]$, which captures how effectively adopters in i can understand the idea in a way that enables application. Each potential adopter is characterized by an idiosyncratic *comprehension requirement*, q, drawn from a uniform distribution over the interval $[0,1]$. This threshold reflects the minimum degree of understanding the adopter needs in order to effectively use the idea for their specific objectives. Adoption occurs if $\Gamma(i) \geq q$, that is, if the adopter's comprehension of the idea exceeds their required level of understanding.[9]

Given the assumptions on the distribution of potential adopters and comprehension requirements, the mass of adopters in field i is simply equal to their degree of comprehension of the idea:

$$\mu(i) = \Gamma(i). \tag{2}$$

2.1.2 Determinants of comprehension

Comprehension depends on three factors: the scientific distance (i) of the adopter's domain from the idea's origin, the idea's intrinsic knowledge depth (k), and the researcher's choice of language accessibility, which we denote by $a > 0$. As discussed above, comprehension declines with both distance and knowledge depth, and the two factors reinforce each other: depth reduces comprehension more at larger distances, and distance has a stronger effect for ideas built on deeper knowledge. Language accessibility generates two opposing forces: a bridging effect, which raises comprehension for distant fields, and a dilution effect, which reduces it for all audiences. Both forces are amplified by knowledge depth.

We capture these interactions by assuming that distance, knowledge depth, and accessibility combine into comprehension through a simple function $\gamma(i,k,a)$, defined as

$$\Gamma(i) = \gamma(i,k,a) \equiv \zeta - \lambda\, k^{\psi}\, a^{-\phi}\, i - \eta\, k\, a, \tag{3}$$

where ζ, λ, η, ψ, and ϕ are positive constants. We assume that k cannot exceed a value $k_{\max} > 0$,

[9] In practice, scientific distance may also directly affect an idea's intrinsic *applicability* across domains. For example, a concept in molecular biology may be more applicable to medicine than to computer science. A natural way of introducing this margin is to assume that adoption occurs if the random draw q is below the product of comprehension and an applicability term that declines exponentially with distance. Since none of the qualitative predictions of the model is affected by this margin, we abstract from this dimension and focus on comprehension (itself a function of scientific distance) as the sole driver of adoption.

representing the highest hypothetical degree of knowledge depth within reach for human cognition, and impose restrictions on the other parameters so that, in equilibrium, $\Gamma(i)$ is positive for all $i \in [0, 1]$ and $k \in [0, k_{\max}]$. Equation (3) defines comprehension as a baseline ζ, capturing the intelligibility of self-evident ideas ($k = 0$), minus two additively separable terms.

The first term, $\lambda\, k^{\psi}\, a^{-\phi}\, i$, grows with both distance and knowledge depth but is mitigated by language accessibility. This term captures the loss in comprehension that arises when a "deep" idea is delivered to an audience with a distant cognitive framework, with the parameter λ controlling the size of this loss and the parameter ψ its elasticity with respect to depth. The *bridging effect* refers to the gain in comprehension produced via this channel by an increase in language accessibility:

$$\text{Bridging effect:} \qquad \frac{\partial(-\lambda\, k^{\psi}\, a^{-\phi}\, i)}{\partial\, a} = \phi\, \lambda\, k^{\psi}\, a^{-\phi-1}\, i > 0,$$

where the parameter ϕ controls the strength of this effect.

The second term, $\eta\, k\, a$, reflects the fact that, regardless of distance, ideas with higher knowledge depth require greater precision and technical detail to be understood in a way that enables effective use. Increasing language accessibility can reduce this precision, creating a *dilution effect* that lowers comprehension for all audiences:

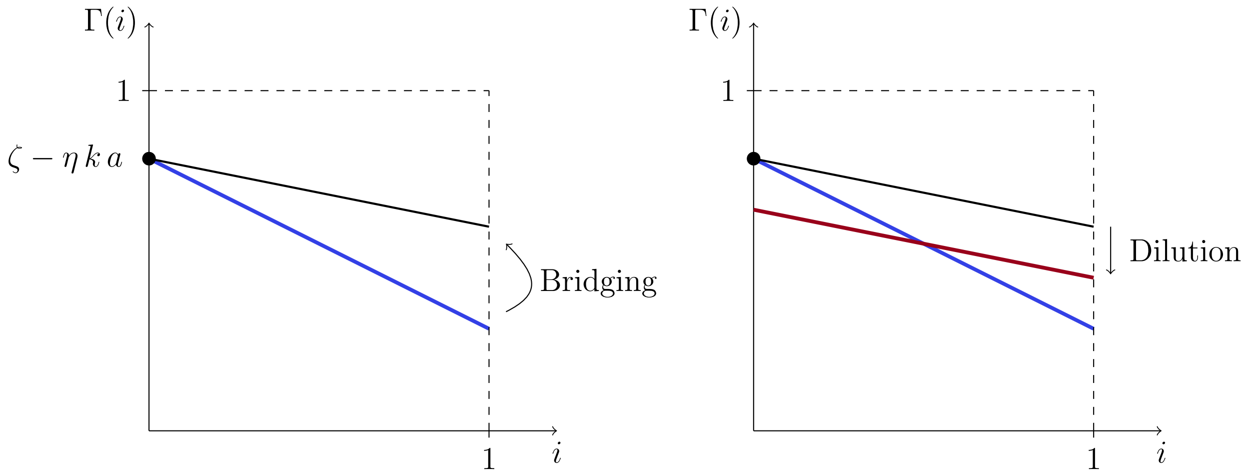
$$\text{Dilution effect:} \qquad \frac{\partial(-\eta\, k\, a)}{\partial\, a} = -\eta\, k < 0.$$

The parameter η controls the size of this loss. Note that we define variables so that the exponents of k and a in the second term are set to one and the elasticities of bridging, ψ and ϕ, are measured relative to this unit benchmark.

Figure 1 illustrates these effects. For a given level of accessibility, comprehension declines linearly with scientific distance. Increasing a affects this relationship in two ways. The bridging effect, shown in the left panel, rotates the comprehension line around the intercept, yielding large gains in $\Gamma(i)$ for distant fields and smaller gains for nearby ones. The dilution effect, shown in the right panel, shifts the line downward, lowering comprehension for all audiences. On net, higher accessibility raises comprehension for sufficiently distant audiences while lowering it for nearby ones.

Higher knowledge depth magnifies both the costs of dilution and the benefits of bridging, as illustrated in Figure 2. The figure depicts how an increase in accessibility affects ideas of different knowledge depth. For low-depth ideas (left panel), which are close to basic principles, comprehen-

Figure 1: **Effect of an increase in language accessibility: bridging and dilution**



Notes: The figure illustrates how an increase in language accessibility affects comprehension across fields at varying scientific distance, holding knowledge depth fixed. The left panel shows the bridging effect: the comprehension line rotates around the intercept. The right panel shows the dilution effect: comprehension declines for all audiences.

sion is broadly high and declines only modestly with distance. In this case, language plays a limited role: raising accessibility from a_{low} to a_{high} produces only small gains for distant audiences and small losses for nearby ones. By contrast, for high-depth ideas (right panel), comprehension falls steeply with distance. Here, greater accessibility generates a strong bridging effect that improves comprehension for distant fields, but also a substantial dilution effect that reduces it for nearby audiences.

2.1.3 The researcher's problem

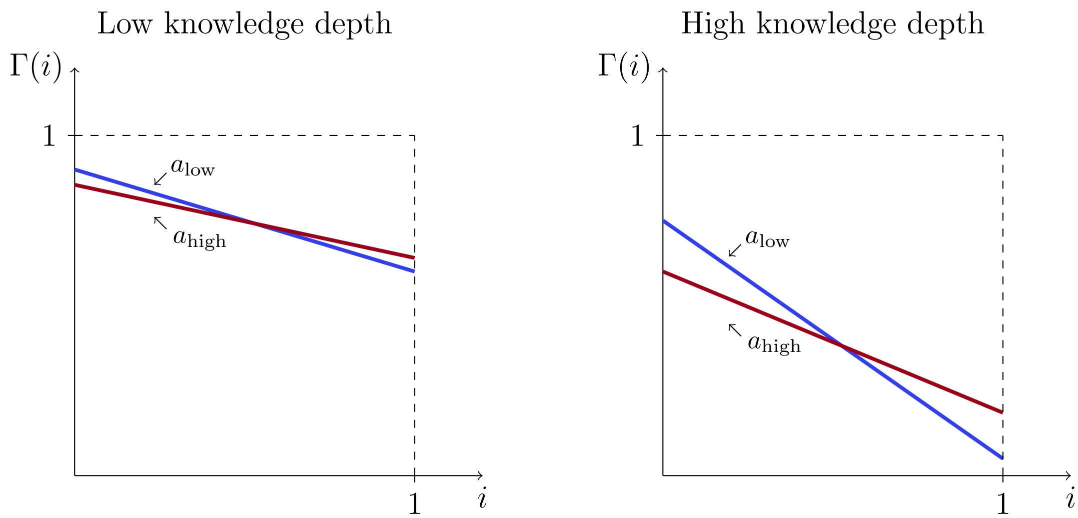
The researcher is intrinsically motivated by the adoption of the new idea but has an own-field bias, meaning that adoption by nearby fields is valued more than adoption by distant ones. Formally, the researcher's utility, U, equals the weighted mass of adopters across domains, where the weight given to each domain decays exponentially with distance:

$$U = \int_0^1 e^{-\delta i}\, \mu(i)\, \mathrm{d}i, \tag{4}$$

where $\delta \geq 0$ measures the degree of own-field bias. As illustrated in Figure 3, own-field bias introduces a wedge between the social and private weighting of adoption across fields. The social planner values adoption uniformly across domains, while the researcher discounts adoption by more distant fields. This wedge is zero in the origin field ($i = 0$) and increases with scientific distance.

After the idea is developed, the researcher chooses a level of language accessibility a to maximize

Figure 2: **How bridging and dilution vary with knowledge depth**



Notes: The figure shows the effect of language accessibility on comprehension across fields at varying scientific distance, for two different levels of knowledge depth. The left panel shows this effect for a low-depth idea; the right panel for a high-depth idea. Language accessibility has a larger effect when ideas have higher knowledge depth. When concepts are closer to self-evident statements, the choice of language has a modest impact on comprehension.

utility. Given the adoption process and the utility in Equation (4), the researcher's problem can be written as

$$\max_{a>0} \int_0^1 e^{-\delta i}\, \gamma(i,k,a)\, \mathrm{d}i. \tag{5}$$

Substituting the functional form of $\gamma(i,k,a)$ into Equation (5) and taking first-order conditions yields

$$\underbrace{\int_0^1 e^{-\delta i}\, \phi\, \lambda\, k^{\psi}\, a^{-\phi-1}\, i\, \mathrm{d}i}_{\text{Discounted bridging}} = \underbrace{\int_0^1 e^{-\delta i}\, \eta\, k\, \mathrm{d}i}_{\text{Discounted dilution}}, \tag{6}$$

showing that the researcher sets a so that discounted bridging across all audiences (the left-hand side) equals discounted dilution (the right-hand side).

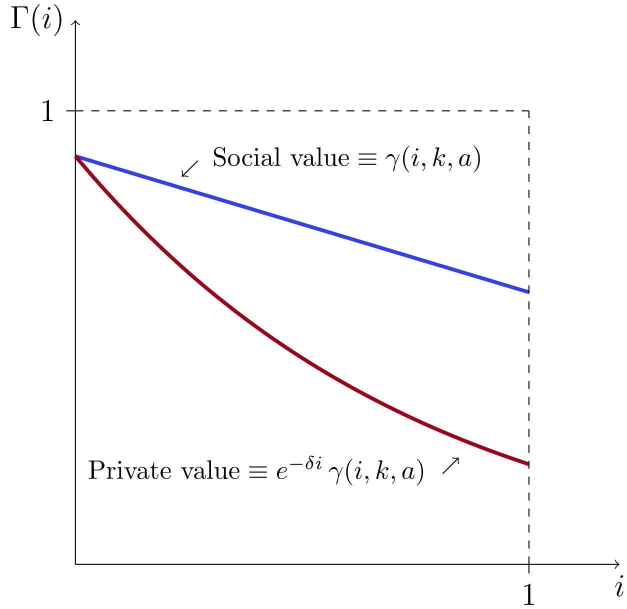
2.2 Model insights

Rearranging Equation (6) gives the optimal choice of accessibility as a function of knowledge depth:

$$a^*(k) = \left(\frac{\phi\, \lambda\, \Omega(\delta)}{\eta}\, k^{\psi-1}\right)^{\frac{1}{\phi+1}}, \tag{7}$$

where $\Omega(\delta) = \frac{1-e^{-\delta}(\delta+1)}{\delta(1-e^{-\delta})}$ is a positive term that monotonically declines with own-field bias δ, hence capturing the value the researcher derives from adoption by external audiences.

Figure 3: **Private and social value of adoption by field**



Notes: The social value generated by the idea in each field is equal to the field-specific adoption rate, $\gamma(i,k,a)$. The researcher has own-field bias $\delta \geq 0$, so their private value from adoption in field i is discounted by a factor $e^{-\delta i}$.

Equation (7) shows how knowledge depth affects the choice of language accessibility. The key parameter is ψ, the elasticity of the bridging effect to knowledge depth relative to the elasticity of the dilution effect (which is set to one). Intuitively, greater depth raises the benefits of accessible language, since accessibility helps convey complex ideas to audiences with distant cognitive frameworks. At the same time, depth magnifies the loss of precision and communicative efficiency that accessible language imposes on nearby audiences. When $\psi < 1$ (meaning the dilution effect is more sensitive to knowledge depth than the bridging effect) the latter force dominates, and higher knowledge depth leads the researcher to choose lower accessibility. The opposite occurs when $\psi > 1$. In summary:

Insight 1. *If the elasticity of dilution to knowledge depth is larger than that of bridging, higher knowledge depth leads to lower language accessibility.*

The equation also shows that, for any given level of knowledge depth, stronger own-field bias (δ) lowers the researcher's choice of accessibility. This is intuitive: higher a always shifts comprehension toward distant audiences at the expense of nearby ones. When the researcher places greater weight on nearby adoption, this tradeoff makes higher accessibility less attractive.

Having characterized the researcher's choice of accessibility, we now examine its implications for total adoption,

$$M \equiv \int_0^1 \mu(i)\,\mathrm{d}i = \int_0^1 \big(\zeta - \lambda\, k^{\psi}\, a^{-\phi}\, i - \eta\, k\, a\big)\,\mathrm{d}i. \tag{8}$$

Plugging $a^*(k)$ into Equation (8) and evaluating the integral gives

$$M = \zeta - \xi\,\Delta(\phi, \underset{+}{\delta})\,k^{\sigma}, \tag{9}$$

where $\xi = \lambda^{\frac{1}{\phi+1}}\,\eta^{\frac{\phi}{\phi+1}}$ and $\sigma = \frac{\phi+\psi}{\phi+1}$ are positive composite constants, and $\Delta(\phi,\delta) > 0$ is monotonically increasing in δ as long as $\delta \geq 0$.[10] Equation (9) shows that greater knowledge depth reduces total adoption, and that this impact is amplified—through the choice of language accessibility—by the degree of own-field bias.

The effect of language accessibility on adoption can be better understood by decomposing M into a within-field component and a component capturing how adoption extends across fields. As we show in Appendix A.1, total adoption can be written as

$$M = \mu(0) \times \Theta(\underset{+}{D}), \tag{10}$$

where $\mu(0)$ denotes the adoption rate in the field of origin ($i = 0$), and

$$D \equiv \frac{1}{M}\int_0^1 \mu(i)\; i\;\mathrm{d}i \tag{11}$$

is the average distance of adopters from the origin field, which we refer to as the *breadth of adoption*. The function $\Theta(\cdot)$ is increasing, reflecting that broader diffusion across fields raises total adoption for a given level of within-field uptake.

This decomposition clarifies how changes in accessibility translate into changes in adoption. For a given level of knowledge depth, a reduction in own-field bias δ raises equilibrium accessibility. When $\delta > 0$, so that the researcher is subject to some degree of own-field bias, Equation (9) implies that this shift toward higher accessibility raises total adoption M. At the same time, higher accessibility reduces adoption in the origin field, $\mu(0)$, by lowering comprehension for nearby audiences. Since M rises while $\mu(0)$ falls, the increase in total adoption must come from the cross-field component, $\Theta(D)$, that is, from broader diffusion of the idea across fields:

[10] Specifically, $\Delta(\phi,\delta) = \frac{1}{2}\,(\phi\,\Omega(\delta))^{-\frac{\phi}{\phi+1}} + (\phi\,\Omega(\delta))^{\frac{1}{\phi+1}}$, where $\Omega(\delta) = \frac{1-e^{-\delta}(\delta+1)}{\delta(1-e^{-\delta})}$. It is easy to show that $\Omega(\delta) \in (0, \frac{1}{2})$ for $\delta > 0$, is decreasing in δ, and tends to $\frac{1}{2}$ as δ approaches zero. It is also easy to show that $\Delta(\phi,\delta)$ is decreasing in $\Omega(\delta)$ for $\Omega(\delta) \leq \frac{1}{2}$. It follows that $\Delta(\phi,\delta)$ is monotonically increasing in δ for $\delta \geq 0$.

Insight 2. *Higher language accessibility increases the breadth of adoption.*

Finally, consider the overall effect of knowledge depth on the breadth of adoption once the researcher's optimal choice of accessibility is taken into account. In Appendix A.2, we show that D always decreases with depth. Combining this result with Insights 1 and 2, when the sensitivity of dilution to depth exceeds that of bridging ($\psi < 1$), this decline is amplified by the response of language accessibility:

Insight 3. *Higher knowledge depth lowers the breadth of adoption. If the elasticity of dilution to knowledge depth is larger than that of bridging, lower language accessibility acts as a mediating channel.*

In Appendix A.2, we also show that the narrowing of diffusion is larger when the researcher's own-field bias is stronger. Intuitively, as knowledge depth increases, comprehension declines more steeply with scientific distance. If δ is large, the equilibrium choice of accessibility is systematically tilted downward, promoting adoption in nearby domains at the expense of distant ones. When ideas are close to basic principles, this bias has little effect on diffusion, since comprehension remains high even for far audiences. As the knowledge behind new ideas becomes deeper, however, the bias becomes increasingly costly, reducing the breadth—and hence the level—of adoption.

2.3 Implications for the social value of scientific ideas

These insights have implications for how the social returns to science evolve as knowledge accumulates.

First, as ideas grow more detached from basic principles, their social value declines. In our setting, this happens not because the intrinsic content of new ideas is less valuable, but because the depth of the knowledge on which they are built makes them less comprehensible, reducing their adoption. In this sense, the social returns to science may fall even when the intrinsic value of new ideas rises or remains unchanged.

Second, researchers' own-field bias becomes increasingly costly from a social welfare perspective as the stock of knowledge grows. Even under the socially optimal choice of accessibility—obtained by setting $\delta = 0$ in Equation (7)—breadth would fall with knowledge depth, since ideas lying on deeper knowledge are disproportionately more difficult for distant audiences to understand. Own-field bias amplifies this loss by tilting accessibility toward nearby domains, leaving adoption in distant fields inefficiently low.

We return to these implications in Section 6, where we discuss how institutional incentives for recognition within closely connected fields can shape the diffusion and social value of new ideas.

2.4 Looking ahead: From theory to data

Insights 1–3 show that knowledge depth reduces the breadth of diffusion and, under some conditions, this effect is amplified by changes in communication choices. The key parameter is the elasticity of the bridging effect to depth (ψ) relative to the elasticity of the dilution effect (which is normalized to one). When the sensitivity of bridging is lower than that of dilution ($\psi < 1$), changes in language accessibility reinforce the effect of knowledge depth on diffusion. In the remainder of the paper, we bring these insights to the data to examine how the diffusion of new scientific ideas has evolved over recent decades and how knowledge depth and language accessibility have shaped this process.

We use data on scientific publications to identify newly introduced concepts and trace their diffusion over time and across areas of science. We show that, over the period covered by our data, the depth of knowledge on which new concepts are built has increased, while the accessibility of the language used to introduce them and their breadth of adoption have declined. We then test the key mechanisms highlighted by the model: language accessibility increases the breadth of adoption of new ideas, even after controlling for their intrinsic features, and greater depth narrows diffusion, with changes in language accounting for a substantial portion of the effect.

As a final step, we embed our setting in a simple Romer-style growth model that reproduces the empirical patterns and allows us to study the implications of knowledge accumulation and own-field bias for long-run growth and the social value of science.

3 Data

We combine data from three sources to trace the introduction and diffusion of scientific concepts across fields and over time. Our core dataset consists of publications indexed in PubMed, which we augment with field and topic classifications from OpenAlex and author disambiguation from Author-ity.

3.1 PubMed

Our core dataset is built from the PubMed Baseline Repository maintained by the National Library of Medicine (NLM).[11] The dataset includes information on more than 31 million papers published between 1781 and 2022. For each paper, we extract the date (month and year) of publication, the full abstract, language, journal, and Medical Subject Headings (MeSH) codes.[12] MeSH codes are manually assigned to each paper by librarians at the NLM with the purpose of indexing articles and facilitating searching. Each code identifies an object of study within a hierarchical classification. For our analysis, we consider the second level of the hierarchy (for example, within the highest level identifying "Anatomy," the second level includes "digestive system," "respiratory system," etc.).

3.2 OpenAlex

We collect topic and field data from OpenAlex Topics (Priem et al., 2022), which assigns to each paper categories from the All Science Journal Classification (ASJC). Building upon the classification system developed by the Center for Science and Technology Studies (CWTS), OpenAlex uses the methodology proposed by Waltman and van Eck (2012) to cluster papers into 4,521 categories based on incoming and outgoing citations. It then uses these clusters to train a machine learning procedure that uses a fine-tuned large language model (LLM) and additional paper information, such as journal names, titles, and abstracts, to map each CWTS category to an ASJC field.[13]

Contrary to MeSH codes, which identify the object of the study as it emerges from the title and abstract, the ASJC fields assigned by OpenAlex, being based on citation patterns, capture the scholarly literature in which a paper is situated. For example, a paper focused on the medical causes of HIV may be assigned overlapping MeSH codes as a paper on the social consequences of HIV, but a different ASJC field.

3.3 Author-ity

To disambiguate author names, we rely on the Author-ity dataset (Torvik and Smalheiser, 2009), which clusters author name instances into researcher identities with approximately 98% accuracy,

[11] The NLM produces a baseline set of MEDLINE/PubMed records in XML format that are available for download from their ftp server. Accessed April 2022.

[12] For journals that are published quarterly, we take the first month of the quarter as the publication month.

[13] A detailed description of the procedure is provided in OpenAlex's white paper available at https://docs.google.com/document/d/1bDopkhuGieQ4F8gGNj7sEc8WSE8mvLZS/edit.

covering all PubMed publications up to 2018. The disambiguation relies on a probabilistic model that incorporates both name-specific features (e.g., middle initials, suffixes, email addresses) and article-level metadata (e.g., coauthors, affiliations, journal, MeSH terms).

The algorithm computes pairwise similarity scores for articles sharing the same author name and applies agglomerative clustering to infer individual identities. The method relies only on internal PubMed metadata—rather than external identifiers or manual curation—making it especially suited for large-scale analysis.

3.4 Identifying new scientific concepts

Empirically, we think of new ideas as scientific concepts newly introduced in the literature at a given point in time. Following Bhattacharya and Packalen (2020), we define a new concept as any combination of words appearing in a paper's abstract that had not appeared in the abstracts of earlier publications.

To extract such combinations from the unstructured text containing the abstract, we follow established best practices and proceed in four steps. First, we clean the text by removing numbers, words with fewer than three characters, DNA or RNA sequences, and hyperlinks. We also lemmatize[14] each word and replace instances of British English spelling with its American English equivalent. Second, we split the text into sentences and sub-sentences based on punctuation and stop words. Third, we extract all the combinations of length n of adjacent words (n-grams) obtainable from those sub-sentences, dropping possible duplicates. Fourth, we keep only the n-grams that appear in the Unified Medical Language System (UMLS) (Bodenreider, 2004), a thesaurus of medical terms curated by the National Library of Medicine, and standardize each n-gram using the corresponding entry in the UMLS. This step allows us to uniquely identify a concept, even when different terms or acronyms are used to refer to it (e.g., human immunodeficiency virus and HIV). We then assign each concept a primary MeSH category based on the MeSH codes of the papers introducing the concept; Appendix B describes this assignment in detail.

Appendix Table C.1 lists the most adopted concepts for each decade in our sample. "Immunodeficiency virus" is the most adopted concept, being referenced by 15,189 papers in the first ten years since its introduction in 1986. Appendix Figure D.1 plots the number of new concepts introduced each year by their primary top-level MeSH category. There is no clear time trend in the

[14] Lemmatization is the process of reducing words to their base or dictionary form (called the *lemma*), in a way that makes them insensitive to verb tenses, plurals, and other inflected forms of words. For example, the words *running*, *ran*, and *runs* are all lemmatized to *run*.

overall number of new concepts: the number rises moderately during the first half of the sample and declines afterward, fluctuating between roughly 1,000 and 1,700 concepts per year. Most of this variation is driven by the largest category, "Chemicals and Drugs."

3.5 Embeddings

Our primary measure of diffusion breadth is based on the semantic similarity of the papers introducing and those adopting a new concept. To measure this similarity, we construct vector representations of each abstract using a large-scale embedding model.[15] Embeddings represent text as points in a high-dimensional space, where geometric proximity reflects semantic similarity. Compared to traditional approaches such as TF–IDF or bag-of-words, which rely on word frequencies and ignore context, embeddings encode the meaning of words and their relations within sentences. For example, two papers on measles vaccines will appear close to each other even if they use different terminology or stylistic conventions. This property makes embeddings particularly useful for tracking how ideas diffuse across disciplines and over time, when the language used to describe them may change.

3.6 Sample

Our final sample includes all papers in PubMed published between 1970 and 2019, with English-language abstracts and whose domain, as assigned by OpenAlex, falls within the "Health Sciences" or "Life Sciences". We focus on new scientific concepts introduced between 1980 and 2009. Papers from 1970-1979 serve as a burn-in period to construct a baseline dictionary of pre-existing concepts, while papers from 2010-2019 are excluded from the identification of new concepts but included as potential adopters of earlier ones. Appendix B provides more details on the data and sample construction.

4 Measurement and trends

Our theory predicts that rising knowledge depth lowers the breadth of adoption, with the effect being amplified, under certain parameter conditions, by worsening language accessibility. In the

[15] In particular, we obtain these representations using OpenAI's `text-embedding-3-large` model, which maps each abstract to a 3,072-dimensional vector. Recent work shows that empirical measures of textual similarity can vary substantially across embedding models, including in patent applications (Ganguli et al., 2026). For this reason, we validate our results using BioBERT, a language model trained on biomedical text (Lee et al., 2020).

remainder of the paper, we confront these predictions empirically. In this section, we introduce the empirical measures of the key objects in the model and study their evolution over time throughout the period covered by our sample. In Section 5, we will use these measures to formally test the mechanisms highlighted by our theory.

4.1 Empirical model

Throughout this section, the unit of analysis is a new scientific concept introduced between 1980 and 2009, identified as described in Section 3.4.

For each concept c, we construct two related sets of papers. First, we define the set of *breakthrough* papers, denoted by $\mathcal{B}(c)$, as those that use concept c within one year of its first appearance in the literature. These papers contributed to the initial development of the idea, either by introducing it or by adopting it very early. Second, we define the set of *adopter* papers, denoted by $\mathcal{A}(c)$, as those that use the concept within ten years of its introduction.

We estimate regressions of the form:

$$Y_c = \beta_{\mathcal{T}(c)} + X_{\mathcal{P}(c)} + W_{\mathcal{M}(c)} + Z_{|\mathcal{N}(c)|} + \epsilon_c, \tag{12}$$

where Y_c denotes a concept-level outcome—such as its knowledge depth, language accessibility, or breadth of diffusion—as defined in the remainder of this section. The coefficients $\beta_{\mathcal{T}(c)}$ capture year-specific effects based on the concept's introduction year $\mathcal{T}(c)$ and constitute our main objects of interest, as they trace how concept-level outcomes have changed over time.

Equation (12) includes a rich set of controls. The term $X_{\mathcal{P}(c)}$ is a fixed effect that flexibly accounts for heterogeneity in the outcome arising from differences in the number of breakthrough and adopter papers. Specifically, we classify each concept c into one of 1,600 categories, $\mathcal{P}(c)$, defined by the interaction of 40 bins of $|\mathcal{B}(c)|$ and 40 bins of $|\mathcal{A}(c)|$. This fixed effect absorbs variation associated with a concept's intrinsic features, such as its quality and early visibility, as well as mechanical effects driven by the size of the sets of breakthrough and adopter papers. The term $W_{\mathcal{M}(c)}$ denotes a fixed effect for the primary MeSH code among the breakthrough papers associated with concept c, which we denote by $\mathcal{M}(c)$. This control accounts for systematic differences across subject areas in patterns of knowledge depth, language use, and diffusion. Finally, the term $Z_{|\mathcal{N}(c)|}$ is a fixed effect for the number of breakthrough authors of concept c, whose set we denote by $\mathcal{N}(c)$, flexibly accounting for mechanical differences that may arise when aggregating author-level measures to the concept level.

The estimation sample includes all concepts introduced between 1980 and 2009 that have at least three adopter papers within ten years of their introduction. For instance, a concept first appearing in 1980 may have adopters from 1981 to 1990, while one introduced in 2009 may have adopters from 2010 to 2019. We cluster standard errors at the level of the interaction between the concept's introduction year $\mathcal{T}(c)$ and its dominant MeSH code $\mathcal{M}(c)$, allowing for arbitrary correlation of residuals within these groups.

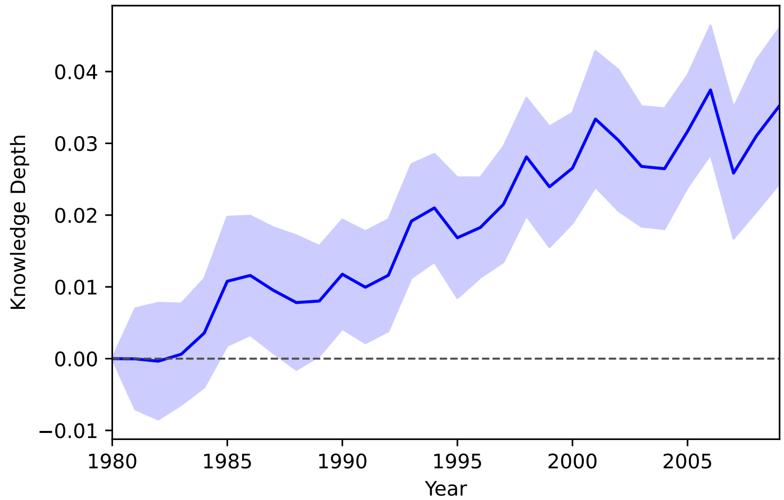
4.2 Knowledge depth

As knowledge accumulates and low-hanging fruits are exhausted, pushing the frontier requires the combination of ideas that are farther removed from basic principles. Charles Darwin could formulate the theory of natural selection largely on his own, relying on simple empirical observations and reasoning, even without any knowledge of genetics. This contrasts with the large-scale collaborations that have driven recent advances in molecular biology: the mapping of the human genome involved the coordinated work of thousands of scientists (IHGSC, 2001), and breakthroughs such as CRISPR-based gene editing and the development of AlphaFold have relied on the combined contributions of many specialized research teams.

In our framework, we take this rise in knowledge depth as the fundamental force underlying changes in diffusion. While directly measuring the knowledge depth of a concept is challenging in the absence of domain-specific expertise, we construct a concept-level measure based on a simple intuition. Following Jones (2009), who shows that deeper knowledge is reflected in higher individual specialization, we use the degree of specialization of the scientists introducing a new concept as an observable proxy. Because research built on deeper layers of prior work tends to require narrower expertise, concepts introduced by highly specialized researchers can be interpreted as stemming from deeper underlying ideas (Wuchty et al., 2007; Agrawal et al., 2016).

For each author of a breakthrough paper, we compute the Herfindahl-Hirschman Index (HHI) of the distribution of that author's publications across fields—as defined by OpenAlex—in the five years preceding the breakthrough. To remove mechanical effects related to differences in publication counts, we regress the HHI on a set of fixed effects for the number of authored papers. The residual of this regression provides a measure of individual specialization. We then construct a concept-level proxy for knowledge depth, K_c, as the average individual specialization of all authors

Figure 4: **Knowledge depth (individual specialization) of newly introduced concepts: 1980-2009**



Notes: The figure plots point estimates and 95% confidence intervals of β_t from Equation (12), where the outcome K_c is defined as the average across the authors of the breakthrough papers of concept c of their individual specialization. Standard errors are clustered at the level of the concept's introduction year interacted with the primary MeSH code. $N = 39,837$. $R^2 = 0.052$.

of a concept's breakthrough papers:

$$K_c = \frac{1}{|\mathcal{N}(c)|} \sum_{n \in \mathcal{N}(c)} \text{Specialization}_{n,\mathcal{T}(c)}.$$

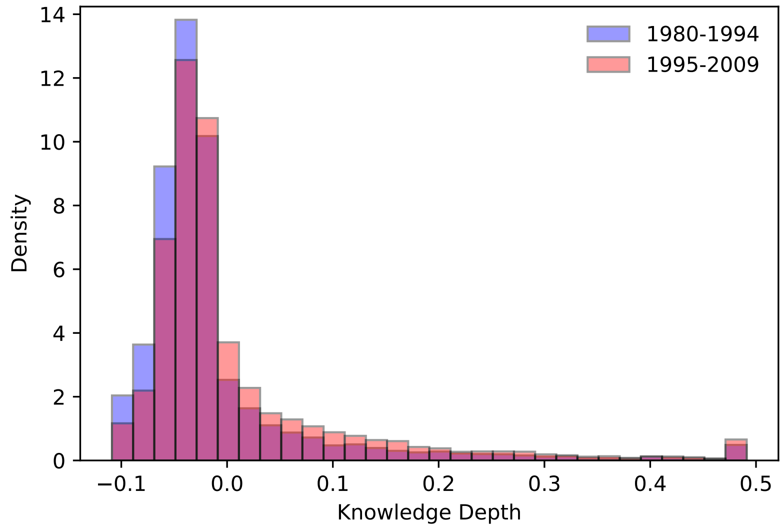
Because the distribution of this measure is markedly right-skewed, we winsorize the upper tail at the 1% level.

We examine how this measure of knowledge depth has evolved over the period covered by our sample by estimating Equation (12) with concept-level knowledge depth K_c as the outcome variable. Figure 4 plots the estimated year fixed effects β_t and their 95% confidence intervals. The estimates are expressed relative to 1980, which is the omitted category (i.e., β_{1980} is normalized to zero). The plot shows a pronounced upward trend: on average, knowledge depth increases by approximately 0.04 points over the sample period, a substantial change given that the standard deviation of the measure is 0.11.[16]

Figure 5 plots the distribution of the knowledge depth measure across all concepts, separating those introduced earlier in the sample period (1980–1994, blue) from those introduced later (1995–2009, pink). The figure shows a clear rightward shift in the distribution, with little change

[16] This finding is not itself novel, as the increase of knowledge depth over time is well documented in the literature on the burden of knowledge (e.g., Jones, 2009). Rather, the goal here is to confirm that our measure behaves consistently with established findings, which we take as evidence of the validity of our proxy.

Figure 5: **Knowledge depth (individual specialization) of newly introduced concepts: 1980-1994 vs 1995-2009**



Notes: The figure shows the distribution of the average individual specialization of all authors of each concept's breakthrough papers. Individual specialization is computed as the Herfindahl-Hirschman Index (HHI) of the distribution of the author's publications across (OpenAlex) fields in the five years preceding the breakthrough. The measure is right-winsorized at the 1% level. Concepts are divided into an early (1980–1994, blue) and a late (1995–2009, pink) parts of the sample.

in its shape or dispersion. This pattern indicates that rising knowledge depth is a pervasive feature of newly introduced ideas, and is not driven by a narrow subset of high-depth concepts.

4.3 Language accessibility

Contrary to knowledge depth—which we treat as an inherent property of a new idea, determined by the state of scientific knowledge—language accessibility reflects a deliberate choice by researchers. In communicating their work, scientists balance the need for technical precision against the goal of being understood by wider audiences. How this tradeoff is resolved depends on researchers' objectives and the nature of their ideas, which change over time as the scientific landscape evolves.

Public discussions have long suggested that scientific language has become increasingly impenetrable, with frequent concerns that papers are harder to read and less accessible to non-specialists. A growing body of empirical evidence supports this view. Hayes (1992) documents a rise in lexical difficulty in scientific journals throughout the twentieth century, with the largest increases occurring in general-science outlets such as *Nature* and *Science*. Plavén-Sigray et al. (2017) show that readability in scientific articles has declined steadily since the late nineteenth century, driven primarily by the growing prevalence of technical terminology. Similarly, Barnett and Doubleday

(2020) document an increase in the use of acronyms in recent decades. Despite this evidence, however, the underlying drivers of this trend and its implications for how new ideas diffuse remain poorly understood.

To address this gap, we incorporate language accessibility into our empirical framework through a concept-level measure based on the prevalence of common, non-technical words in the abstracts of papers introducing new concepts. Formally, for each paper b in the set of breakthrough papers $\mathcal{B}(c)$ associated with concept c, we compute the share of words in its abstract that appear in at least 0.1% of all non-breakthrough abstracts published in the year of the concept's introduction, $\mathcal{T}(c)$. The degree of language accessibility of concept c, denoted by A_c, is then defined as the median share of common words across its breakthrough papers:

$$A_c = \text{Median}\left(\left\{\frac{\#\text{ common words}_b}{\text{Total words}_b}\right\}_{b\in\mathcal{B}(c)}\right)$$

Across the concepts used in the main analysis, the average degree of accessibility is 81.4%.[17]

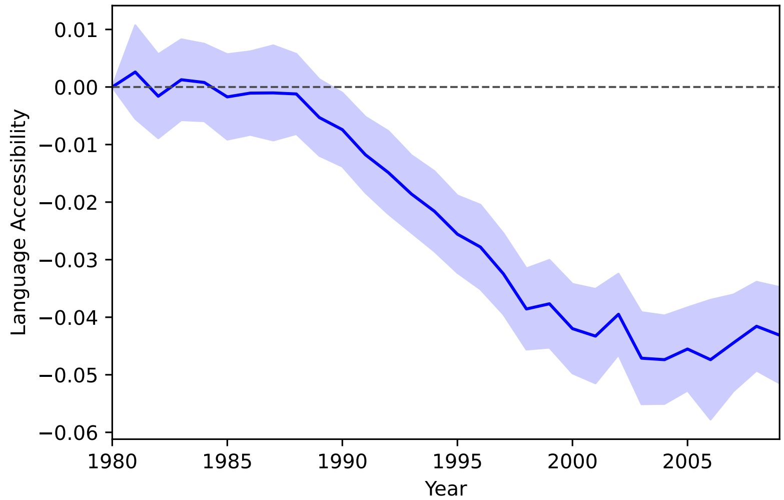
Our measure differs from traditional readability indices commonly used in the literature, such as the Flesch Reading Ease and Flesch–Kincaid measures. These indices are based primarily on sentence length and word length and were originally designed to classify texts according to the educational level required to understand them. In scientific writing, however, accessibility is constrained more by specialized terminology and technical vocabulary than by the complexity of sentence structure. As a result, scientific articles can be highly inaccessible even when they score favorably according to conventional readability measures.

To illustrate the notion of language accessibility captured by our measure, Appendix Figure E.1 displays the abstract of an influential paper published in *Cell* in 1996 that had accumulated more than 6,000 citations on Google Scholar as of June 2026 (Lemaitre et al., 1996). The paper was among the first to establish the role of the Toll signaling pathway, a key component of immune defense, in the fruit fly (*Drosophila*), a discovery that later formed part of the scientific foundation for Jules Hoffmann's Nobel Prize in Physiology or Medicine in 2011.[18] Despite its scientific impact, the abstract relies heavily on technical language that would be difficult for readers outside the field to interpret, and our measure assigns it an accessibility score of only 77.9%, compared to a median of 82.8% among breakthrough papers in our sample. For comparison, Appendix Figure E.2 displays

[17]For 40 concepts (less than 0.1% of the total), this measure equals 100%, meaning that all words in their breakthrough abstracts are classified as common according to our definition.

[18]https://www.nobelprize.org/prizes/medicine/2011/summary/.

Figure 6: **Language accessibility of newly introduced concepts: 1980-2009**



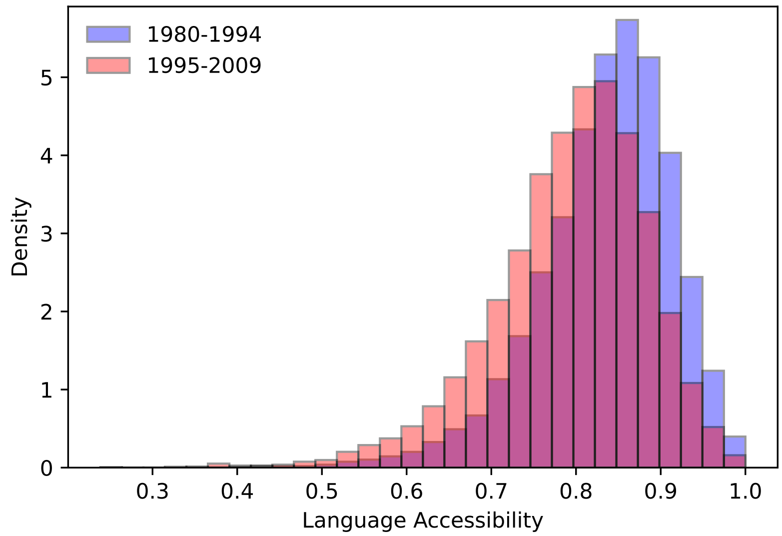
Notes: The figure plots point estimates and 95% confidence intervals of β_t from Equation (12), where the outcome A_c is defined as the median across the breakthrough abstracts of concept c of the share of words found in at least 0.1% of the non-breakthrough abstracts published in $\mathcal{T}(c)$. Standard errors are clustered at the level of the concept's introduction year interacted with the primary MeSH code. $N = 42,470$. $R^2 = 0.223$.

a version generated by a large language model prompted to rewrite the abstract in more accessible language while preserving its substantive content (the exact prompt is shown in the same figure). The rewritten version achieves an accessibility score of 92.7%. The comparison illustrates how substantial differences in measured accessibility can arise solely from changes in how the same ideas are communicated, even when the substance of the idea remains unchanged.

We examine how language accessibility has evolved over time by estimating Equation (12) with concept-level accessibility, A_c, as the outcome variable. Figure 6 reports the estimated year fixed effects β_t from 1980 to 2009, along with 95% confidence intervals. The plot reveals a steady decline in the prevalence of common words in the abstracts of papers introducing new concepts. By 2009, the share of common words had fallen by roughly 4 percentage points relative to 1980. Given that the standard deviation of the measure across the full sample is 8.8%, this represents a meaningful shift toward more specialized and less accessible scientific language.

This pattern reflects a broad change rather than the emergence of a few exceptionally impenetrable papers. Figure 7 shows the distribution of the accessibility measure across all concepts, separating those introduced early in the period (1980–1994, blue) from those introduced later (1995–2009, pink). The entire distribution shifts leftward with little change in shape or dispersion, indicating a widespread decline in language accessibility. On average, the share of common words falls from 83.4% in the early period to 79.3% in the later one.

Figure 7: **Language accessibility of newly introduced concepts: 1980-1994 vs 1995-2009**



Notes: The figure shows the distribution of the median across the breakthrough abstracts of each concept c of the share of words found in at least 0.1% of the abstracts published between $\mathcal{T}(c) - 5$ and $\mathcal{T}(c) - 1$, separating the early (1980–1994, blue) and the late (1995–2009, pink) parts of the sample.

4.4 Breadth of adoption

Having documented trends in the knowledge depth of new ideas and in the language used to communicate them, we now turn to their implications for diffusion. In our setting, the breadth of adoption captures how widely a new scientific concept spreads across potential users once introduced. Our theory predicts that rising knowledge depth narrows the breadth of adoption, while language accessibility can either attenuate or reinforce this effect depending on how scientists choose to communicate their work. In this subsection, we document how the breadth of adoption of new concepts has evolved over time, and in Section 5 we will study empirically how these patterns are linked to the trends in knowledge depth and language accessibility.

To quantify the breadth of adoption of a new concept, we begin by measuring the semantic distance between each pair of its breakthrough and adopter papers using the cosine distance between their abstract embeddings, which we denote by $\mathbf{e}(b)$ and $\mathbf{e}(a)$, respectively:

$$d(b, a) = 1 - \frac{\mathbf{e}(b) \cdot \mathbf{e}(a)}{\|\mathbf{e}(b)\| \|\mathbf{e}(a)\|} \qquad b \in \mathcal{B}(c),\, a \in \mathcal{A}(c).$$

To build intuition for this measure, Appendix Figure E.3 displays the abstracts of three papers conducting research at increasing degrees of scientific distance from the influential *Cell* paper discussed in the previous subsection. The first belongs to the same narrow area of *Drosophila* innate immunity and has a cosine distance of 0.334 from the *Cell* paper. The second studies innate immune responses in mammals and lies within the same broad scientific field, but a different subfield, yielding a distance of 0.575. The third comes from a largely unrelated area of biomedical research and has a distance of 0.738. For comparison, the accessible version of the *Cell* abstract discussed above has a distance of only 0.196 from the original version. As scientific content becomes more distant, cosine distances increase substantially, whereas changes in language that preserve the underlying ideas generate much smaller differences.

Having obtained pairwise distances for all breakthrough–adopter combinations associated with a concept, we summarize their distribution using a single statistic, the concept-level breadth of adoption D_c, defined as the median pairwise cosine distance:

$$D_c = \text{Median}\left(\{d(b,a)\}_{b \in \mathcal{B}(c),\, a \in \mathcal{A}(c)}\right).$$

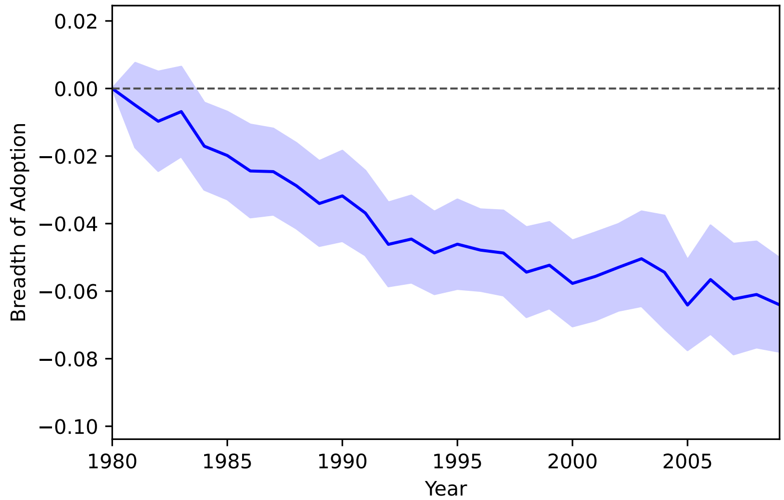
For each concept c, this statistic is computed over all $|\mathcal{A}(c)| \times |\mathcal{B}(c)|$ breakthrough–adopter pairs. Larger values of D_c indicate that adopters are semantically farther from the original breakthroughs and therefore correspond to broader diffusion across scientific domains. We then estimate Equation (12) using this concept-level measure of diffusion breadth as the outcome variable.

Figure 8 plots the estimated year fixed effects β_t from 1980 to 2009, along with their 95% confidence intervals. The figure reveals a steady and pronounced decline in the semantic distance between the papers introducing a new concept and those adopting it over the subsequent decade. The magnitude of the decline is substantial: by 2009, the median cosine distance between adopters and breakthrough papers is about 0.06 lower than in 1980, corresponding to roughly half of the standard deviation of the diffusion measure in the full sample (0.126).

An important question is whether the decline in the breadth of adoption reflects a small subset of concepts with exceptionally narrow diffusion, or instead a broader shift affecting the entire distribution. Figure 9 addresses this question by plotting the distribution of diffusion measures for two equally sized time windows: 1980–1994 (blue) and 1995–2009 (pink). The figure shows a nearly uniform leftward shift in the distribution, with no visible change in its shape or dispersion, pointing to a systematic narrowing in how widely new ideas diffuse.

A potential concern with the patterns shown in Figures 8 and 9 is that the observed decline in the semantic distance between breakthrough and adopter papers may reflect a general shift in language use, objects of study, and methodologies over time rather than a change in the breadth of adoption of new ideas. Because our diffusion measure is based on cosine distances between

Figure 8: **Breadth of adoption of newly introduced concepts: 1980-2009**



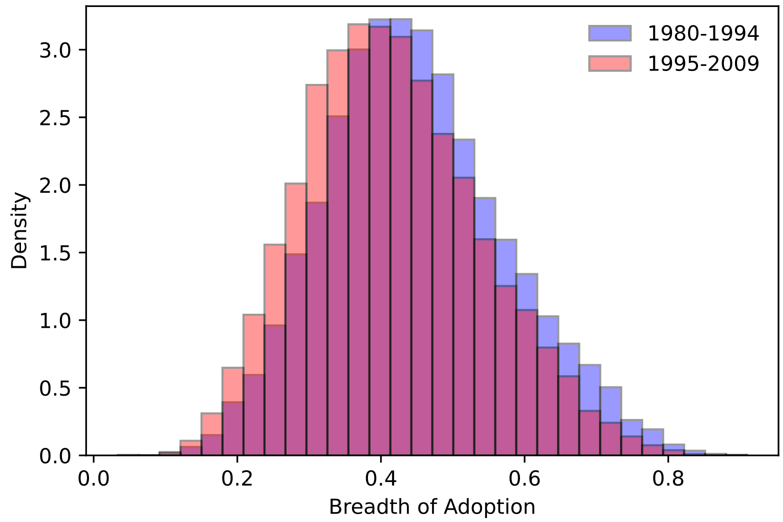
Notes: The figure plots point estimates and 95% confidence intervals of β_t from Equation (12), where the outcome D_c is defined as the median of the pairwise cosine distances between the breakthrough and adopters of concept k. Standard errors are clustered at the level of the concept's introduction year interacted with the primary MeSH code. $N = 42,470$. $R^2 = 0.086$.

text embeddings, increasing uniformity in those dimensions could mechanically reduce measured distances, even if the underlying spread of ideas remained unchanged.

To address this concern, we conduct a set of placebo simulations. For each concept c, we assign a set of simulated adopter papers drawn at random under the constraint that their publication year and primary MeSH code match those of the actual adopters. For each simulation s, we compute the corresponding diffusion measure $\hat{D}_{c,s}$ and then use these simulated measures to estimate year fixed effects β_t from Equation (12). Comparing the observed diffusion trends to these simulated benchmarks allows us to separate changes in adoption breadth from those arising from broader shifts in semantic similarity.

Figure 10 presents the results from the placebo exercise. The red line plots the average of the estimated β_t, together with their minimum and maximum, across 12 simulations. This series exhibits a mild upward trend, suggesting that scientific papers have not become more semantically uniform since 1980, consistent with analogous patterns documented for patent data by Ganguli et al. (2026). The green line shows the estimates of β_t when the outcome variable is defined as the adjusted diffusion measure, $\tilde{D}_c$, calculated for each concept as the difference between the actual (D_c) and average simulated ($\bar{D}_c$) breadth of adoption. This series displays a clear downward trend, closely mirroring the baseline estimates shown in blue. These results confirm that the decline in measured diffusion is not driven by general changes in language, methods, or objects of study, but

Figure 9: **Breadth of adoption of newly introduced concepts: 1980-1994 vs 1995-2009**



Notes: The figure shows the distribution of the median cosine distance between breakthrough and adopters across concepts, separating the early (1980–1994, blue) and the late (1995–2009, pink) parts of the sample.

instead reflects an effective reduction in the breadth of adoption of new scientific ideas.[19]

4.5 From measurement to mechanisms

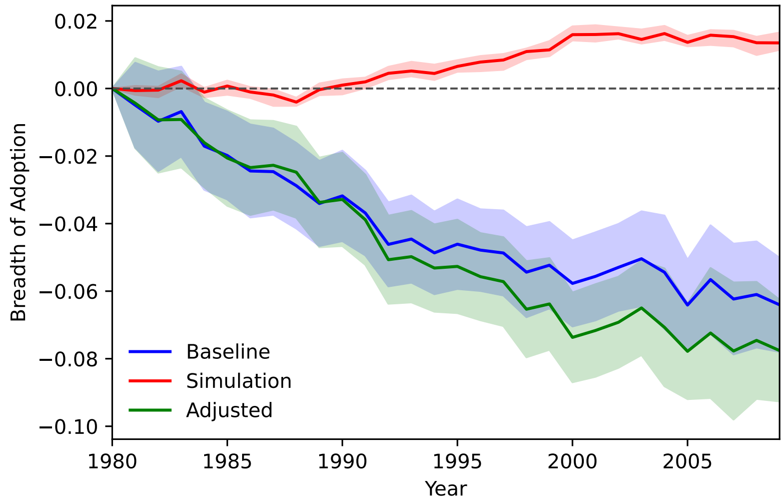
This section has documented three broad trends in the introduction and diffusion of new scientific ideas. The knowledge depth of frontier research has risen steadily over time; the language used to communicate new ideas has become less accessible; and the breadth of adoption of new concepts has declined, indicating that new ideas now spread across a narrower range of potential users. While descriptive, these patterns align closely with the mechanisms highlighted by our theory: rising knowledge depth reduces diffusion both directly and indirectly, through researchers' responses in communication choices. The next step is to examine these relationships explicitly.

5 Testing the model's predictions

In this section, we test the model's central predictions linking knowledge depth, language accessibility, and the breadth of adoption of new ideas. We begin by examining whether ideas lying on deeper knowledge are expressed in less accessible language, which provides evidence on whether the dilution effect is more sensitive to knowledge depth than the bridging effect (Insight 1). Next, we

[19]Appendix Figure D.2 shows that producing embeddings using the BioBERT model (Lee et al., 2020) delivers results that are very consistent with those in Figure 10.

Figure 10: **Breadth of adoption of newly introduced concepts: Data vs Simulations**



Notes: The blue and green lines plot point estimates and 95% confidence intervals of β_t from Equation (12). Blue line: the outcome is defined as D_c, i.e., the median of the pairwise cosine distances between the breakthrough and adopters of concept c ($R^2 = 0.086$). Green line: the outcome is defined as $\tilde{D}_c = D_c - \bar{D}_c$, that is, the difference between the median of the pairwise cosine distances between the breakthrough and adopters of concept c, and the corresponding average across 12 simulations ($R^2 = 0.112$). The red line plots the average point estimates of β_t from Equation (12) for the 12 simulations, together with the minimum and maximum estimate, where the outcome in each estimation s is defined as $\hat{D}_{c,s}$. Standard errors are clustered at the level of the concept's introduction year interacted with the primary MeSH code. $N = 42,470$.

test the model's prediction that language accessibility increases the breadth of adoption (Insight 2). Finally, we assess the overall effect of knowledge depth on diffusion (Insight 3) and the extent to which this effect operates through changes in language accessibility. These results connect the empirical trends documented above to the theoretical mechanisms highlighted in our model.

5.1 Ideas built on deeper knowledge are communicated in less accessible language

Our theory suggests that the relationship between knowledge depth and language accessibility reflects the balance of two opposing forces. Simplifying language makes ideas more comprehensible to outsiders (bridging) but reduces precision and technical rigor (dilution). Because both forces are amplified by knowledge depth, the net effect depends on which one grows faster. If the cost of dilution rises more steeply than the benefit of bridging (i.e., if $\psi < 1$), scientists introducing ideas with greater knowledge depth will use less accessible language. Whether this condition holds in practice is an empirical question, to which we now turn.

The aggregate trends documented above, while consistent with a negative effect of knowledge depth on language accessibility, may reflect underlying factors—whether common or independent, and whether operating at the aggregate or subject-area level—influencing both variables. To isolate the direct link between them, we estimate their relationship using a specification that controls for year fixed effects interacted with the primary MeSH code associated with each concept:

$$A_c = X_{\mathcal{P}(c)} + \tilde{W}_{\mathcal{M}(c),\mathcal{T}(c)} + Z_{|\mathcal{N}(c)|} + \theta\, K_c + \epsilon_c. \tag{13}$$

The coefficient θ captures the effect of concept-level knowledge depth (K_c) on language accessibility (A_c), net of period-specific effects that vary across subject areas ($\tilde{W}_{\mathcal{M}(c),\mathcal{T}(c)}$), as well as flexible controls for other concept-level characteristics ($X_{\mathcal{P}(c)}$ and $\tilde{Z}_{|\mathcal{N}(c)|}$).

Table 1 reports the results, progressively adding fixed effects from Equation (13). Column 1 includes only basic concept-level controls (the number of breakthrough authors and the interaction between the number of breakthrough and adopter papers). The estimated coefficient on knowledge depth is negative and statistically significant. Quantitatively, an increase in knowledge depth of one standard deviation is associated with a decline in language accessibility of 7 percent of a standard deviation.

Adding fixed effects for the primary MeSH code in column 2 and interacting them with year fixed effects in column 3 reduces the magnitude of the coefficient by more than half. This attenuation suggests that much of the raw correlation between knowledge depth and accessibility reflects shared time trends and systematic differences across subject areas (if knowledge depth itself partly drives those differences, these controls may remove some meaningful variation). After accounting for these factors, however, the coefficient remains negative and statistically significant, indicating that, even within periods and subject areas, deeper ideas tend to be communicated in less accessible language.

Viewed through the lens of the model, these findings are consistent with the fact that the sensitivity of the dilution effect to knowledge depth exceeds that of the bridging effect (i.e., $\psi < 1$). In other words, as ideas grow more detached from basic principles, the cost of simplifying language rises more steeply than the benefit of reaching broader audiences, prompting scientists to use language that is more technical and less accessible.

5.2 Language accessibility increases the breadth of adoption

In our model, more accessible language facilitates the adoption of ideas by scientists who are farther from the originating field by improving comprehension and lowering barriers to use, expanding

Table 1: **Knowledge depth and language accessibility of newly introduced concepts**

	Language accessibility		
	(1)	(2)	(3)
Knowledge depth	-0.061***	-0.047***	-0.028***
	(0.006)	(0.005)	(0.005)
N	39,807	39,807	39,268
R^2	0.068	0.188	0.298
# brkthr authors f.e.	✓	✓	✓
# brkthr × adopter papers cat.	✓	✓	✓
Primary MeSH f.e.	×	✓	×
Primary MeSH × Year f.e.	×	×	✓

Notes: Standard errors clustered at the year-primary MeSH level in parenthesis. $^{***}p < 0.01$.

diffusion across fields. We now test this prediction empirically.

As a first step, we estimate the relationship between the adjusted breadth of adoption of a new concept, $\tilde{D}_c$, and its language accessibility, A_c:

$$\tilde{D}_c = X_{\mathcal{P}(c)} + \tilde{W}_{\mathcal{M}(c),\mathcal{T}(c)} + Z_{|\mathcal{N}(c)|} + \theta\, A_c + \epsilon_c. \tag{14}$$

A positive estimate of θ indicates that concepts expressed in more accessible language tend to diffuse more broadly. As in Equation (13), the specification includes year fixed effects interacted with the primary MeSH code associated with each concept, $\tilde{W}_{\mathcal{M}(c),\mathcal{T}(c)}$, so that comparisons are made among concepts introduced in the same year and subject area but differing in their degree of accessibility.

Table 2 reports the estimates from Equation (14) under different combinations of fixed effects. Across all specifications, the coefficient on accessibility, θ, is positive, statistically significant, and economically meaningful. In column 1, which includes only basic concept-level controls, a one-standard-deviation increase in accessibility is associated an increase in the breadth of adoption of 19% of a standard deviation. Adding fixed effects for the primary MeSH code in column 2 and MeSH-by-year interactions in column 3 reduces the magnitude of the coefficient by roughly one third, yet it remains large and precisely estimated. As in the previous results, this attenuation indicates that part of the raw relationship reflects differences across subject areas and common time

Table 2: **Language accessibility and breadth of adoption of newly introduced concepts**

	Adjusted breadth of adoption		
	(1)	(2)	(3)
Language accessibility	0.275***	0.233***	0.171***
	(0.010)	(0.010)	(0.010)
N	39,807	39,807	39,268
R^2	0.086	0.107	0.190
# brkthr authors f.e.	✓	✓	✓
# brkthr × adopter papers cat.	✓	✓	✓
Primary MeSH f.e.	×	✓	×
Primary MeSH × Year f.e.	×	×	✓

Notes: Standard errors clustered at the year-primary MeSH level in parenthesis. $^{***}p < 0.01$.

trends, but the relationship remains strong once these factors are taken into account. Appendix Table C.2 shows consistent results are obtained when using embeddings from the BioBERT model.

While these results reveal a robust positive relationship between language accessibility and the breadth of adoption, they may still reflect unobserved characteristics of the concepts themselves. Concepts expressed in more accessible language could also be inherently more general or broadly applicable, which would independently lead to wider adoption. To address this concern, we turn to a setting that allows us to control for both the intrinsic attributes of each concept and its relevance across subject areas.

We examine how the adoption of a concept varies across fields as a function of how accessible its language is to potential adopters in those fields. For each concept c and field f (as defined by OpenAlex), we construct a measure of the accessibility of its breakthrough papers $b \in \mathcal{B}(c)$ to readers in field f as the share of words in their abstracts that appear in at least 0.1% of all non-breakthrough abstracts published in field f in year $\mathcal{T}(c)$:

$$A^F_{c,f} = \text{Median}\left(\left\{\frac{\#\text{ common words}_{b,f}}{\text{Total words}_b}\right\}_{b\in\mathcal{B}(c)}\right).$$

This measure captures the field-specific accessibility of concept c to field f, that is, how familiar its language is to researchers working in that field.

Using this measure, we test whether concepts diffuse more readily to fields for which the language used to introduce them is relatively more accessible. Specifically, we estimate the following specification at the concept-field level:

$$D^F_{c,f} = \alpha_c + W^F_{\mathcal{M}(c),f,\mathcal{T}(c)} + \theta\, A^F_{c,f} + \epsilon_{c,f}, \tag{15}$$

where $D^F_{c,f}$ measures the adoption of concept c in field f. The inclusion of concept fixed effects, α_c, absorbs all intrinsic characteristics of each concept—such as novelty, quality, or generality—so that identification comes from within-concept variation across fields. The specification also includes fixed effects for the interaction of the concept's primary MeSH, the receiving field, and the year of introduction, $W^F_{\mathcal{M}(c),f,\mathcal{T}(c)}$, which account for differences in the relevance of subject areas ($\mathcal{M}(c)$) to different fields (f) at the time of a concept's introduction ($\mathcal{T}(c)$).

Table 3 reports the estimates. Across all specifications, the results show that concepts diffuse more strongly to fields for which the language used to introduce them is more accessible, even after controlling for both the intrinsic characteristics of each concept and the relevance of its underlying topic to the receiving field. Column 1 uses the number of adopting papers in field f as the outcome variable. The estimates imply that increasing the share of common words from 0 to 1 raises the number of adopting papers by 2.76. This corresponds to an increase of more than half an adopting paper, on average, for a one-standard-deviation rise in field-specific accessibility (0.25). Column 2 shows that the effect is also substantial on the extensive margin: the probability that a concept is adopted by at least one paper in a field increases by more than 5 percentage points for each standard-deviation increase in accessibility. Column 3 shows that the effect remains both statistically and economically significant when the outcome is defined as the inverse hyperbolic sine of the number of adopters. Interpreting (under the usual caveats) the coefficient as a percentage-change effect, a one-standard-deviation increase in field-specific accessibility leads to an increase of more than 10 percent in the number of adopting papers.

Interpreted within our theory, these findings confirm that higher language accessibility increases the breadth of adoption. By making ideas more comprehensible to researchers outside the originating field, accessible language facilitates diffusion across a wider range of audiences.

5.3 The overall effect of knowledge depth on the breadth of adoption

The results point to a configuration of parameters in which the dilution effect is more sensitive to knowledge depth than the bridging effect ($\psi < 1$). In this environment, rising knowledge depth

Table 3: **Field-specific language accessibility and adoption of newly introduced concepts**

	Adoption of concept k by field f		
	(1) #Adopters	(2) Any adopters	(3) IHS #Adopters
Field-specific language accessibility	2.757*** (0.077)	0.221*** (0.002)	0.437*** (0.004)
N	10,237,530	10,237,530	10,237,530
R^2	0.077	0.272	0.296
Concept f.e.	✓	✓	✓
Primary MeSH × Field × Year f.e.	✓	✓	✓

Notes: Standard errors clustered at the concept level in parenthesis. $^{***}p < 0.01$.

reduces the breadth of adoption both directly and indirectly: deeper ideas are intrinsically harder for external audiences to understand and are also communicated in less accessible language, which further hinders diffusion across fields. As a result, changes in language accessibility amplify the impact of knowledge depth on diffusion.

To test this prediction, we estimate a concept-level regression in which the adjusted breadth of adoption, $\tilde{D}_c$, is the outcome and both knowledge depth, K_c, and language accessibility, A_c, are explanatory variables:

$$\tilde{D}_c = X_{\mathcal{P}(c)} + \tilde{W}_{\mathcal{M}(c),\mathcal{T}(c)} + Z_{|\mathcal{N}(c)|} + \theta_1 K_c + \theta_2 A_c + \epsilon_c. \tag{16}$$

The specification progressively adds the same set of fixed effects as in the previous concept-level regressions, including primary MeSH and MeSH-by-year interactions, ensuring that the estimates are comparable across exercises.

Table 4 presents the results. Across all specifications, knowledge depth has a negative effect on the breadth of adoption, as predicted by our theory. In column 1, which includes only basic concept-level controls, a one-standard-deviation increase in depth is associated with a decline in the breadth of adoption of approximately 5 percent of a standard deviation. Adding language accessibility in column 2 reduces the magnitude of the coefficient on knowledge depth by close to 30 percent, indicating that language accessibility accounts for a substantial portion of the relationship between depth and diffusion. Appendix Table C.3 shows that results are consistent

Table 4: **Knowledge depth, language accessibility, and breadth of adoption**

	Adjusted breadth of adoption					
	(1)	(2)	(3)	(4)	(5)	(6)
Knowledge depth	-0.060***	-0.044***	-0.058***	-0.047***	-0.034***	-0.029***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Language accessibility		0.271***		0.230***		0.170***
		(0.010)		(0.010)		(0.010)
N	39,807	39,807	39,807	39,807	39,268	39,268
R^2	0.056	0.087	0.088	0.108	0.181	0.190
# brkthr authors f.e.	✓	✓	✓	✓	✓	✓
# brkthr × adopt. p. cat.	✓	✓	✓	✓	✓	✓
Primary MeSH f.e.	×	×	✓	✓	×	×
Primary MeSH × Year f.e.	×	×	×	×	✓	✓

Notes: Standard errors clustered at the year-primary MeSH level in parenthesis. $^{***}p < 0.01$.

when using embeddings from the BioBERT model.

Columns 3-6 introduce additional fixed effects for primary MeSH and MeSH-by-year interactions. As expected, these controls absorb part of the variation in both knowledge depth and accessibility, reducing the estimated coefficients. Nevertheless, the effect of depth on diffusion remains negative and statistically significant, and its magnitude continues to be meaningfully attenuated when language accessibility is included. The results therefore point to a robust negative relationship between knowledge depth and the breadth of adoption, with language accessibility acting as an important channel behind this effect.

These findings link the trends documented in Section 4 to the mechanism predicted by the model: as the frontier of knowledge expands and new ideas are built on deeper layers of prior work, scientists use less accessible language, which in turn narrows the diffusion of new ideas. The amplification pattern observed here—where declines in accessibility strengthen the impact of knowledge depth on diffusion—is consistent with an environment in which the dilution effect is more sensitive than the bridging effect. In this configuration, rising knowledge depth reduces the social reach of new ideas both because they are intrinsically harder to understand and because they are communicated in ways that limit their adoption across fields.

6 Transmission of science in a Romer-style model

The empirical evidence presented so far supports the core mechanisms highlighted by our theory: as scientific ideas become more detached from basic principles, they are communicated in less accessible language, which limits their diffusion across fields and, in turn, reduces the social returns to new knowledge. In this section, we study these mechanisms in a simple growth framework to examine their broader implications for the evolution of scientific productivity, the value of knowledge over time, and the role of institutions and policies that govern how science is produced and disseminated.

6.1 Dynamic environment

We embed the static framework of Section 2 in a simple dynamic, Romer-style environment in which the stock of scientific knowledge, K_t, summarizes the state of the economy at time t. Time is discrete. Output, which can be interpreted as both aggregate consumption and welfare, is proportional to the stock of knowledge:

$$Y_t = K_t. \tag{17}$$

There is a continuum of scientific fields, which we assume are symmetric and populated by the same measure of scientists, whose total mass is equal to one. Differently from the static setup, we now represent fields as points uniformly distributed along the circumference of a circle. The arc distance between any two points measures their scientific distance. This representation ensures that all fields are ex-ante (and will also be ex-post) symmetric. The static model can be viewed as an "unwrapped" version of this circle, with the origin field placed at $i = 0$ and its antipode at $i = 1$. Beyond this geometric convenience, all primitives remain unchanged from the static environment.

The stock of scientific knowledge evolves according to:

$$K_{t+1} = K_t + h\, M_t\, K_t, \tag{18}$$

where $h > 0$ is an exogenous term controlling the rate of arrival of new ideas and M_t denotes the rate of adoption of those ideas. As knowledge accumulates, the knowledge depth of new ideas increases. We represent this relationship by postulating an increasing function, $f(K)$, satisfying

$f(0) = 0$ and $\lim_{K\to\infty} f(K) = k_{\max}$. A convenient functional form satisfying these properties is:

$$k_t = f(K_t) \equiv k_{\max}\left(1 - e^{-\rho K_t}\right), \tag{19}$$

where $\rho > 0$ determines the rate at which knowledge depth converges to its theoretical maximum as knowledge accumulates.

In each period, a mass $h\,K_t$ of new ideas with depth k_t is generated by scientists uniformly distributed around the circle. As in Romer (1990), the rate of arrival of ideas is linear in the stock of knowledge. By the law of large numbers, each field receives the same number of ideas. Scientists face the same problem as in the static setting: they choose a level of language accessibility to maximize total discounted adoption (Equation 4), and the adoption process follows exactly the same structure as before (Equations 2 and 3). Because all fields are symmetric, the equilibrium choice of accessibility is identical across fields and follows Equation (7). Given this choice, the total adoption rate of a new idea, M_t, is the same as Equation (9):

$$M_t = \zeta - \xi\,\Delta(\phi, \delta)\,k_t^{\sigma}, \tag{20}$$

where ξ and σ are positive composite parameters, and $\Delta(\phi, \delta)$ is an increasing function of the own-field bias δ.

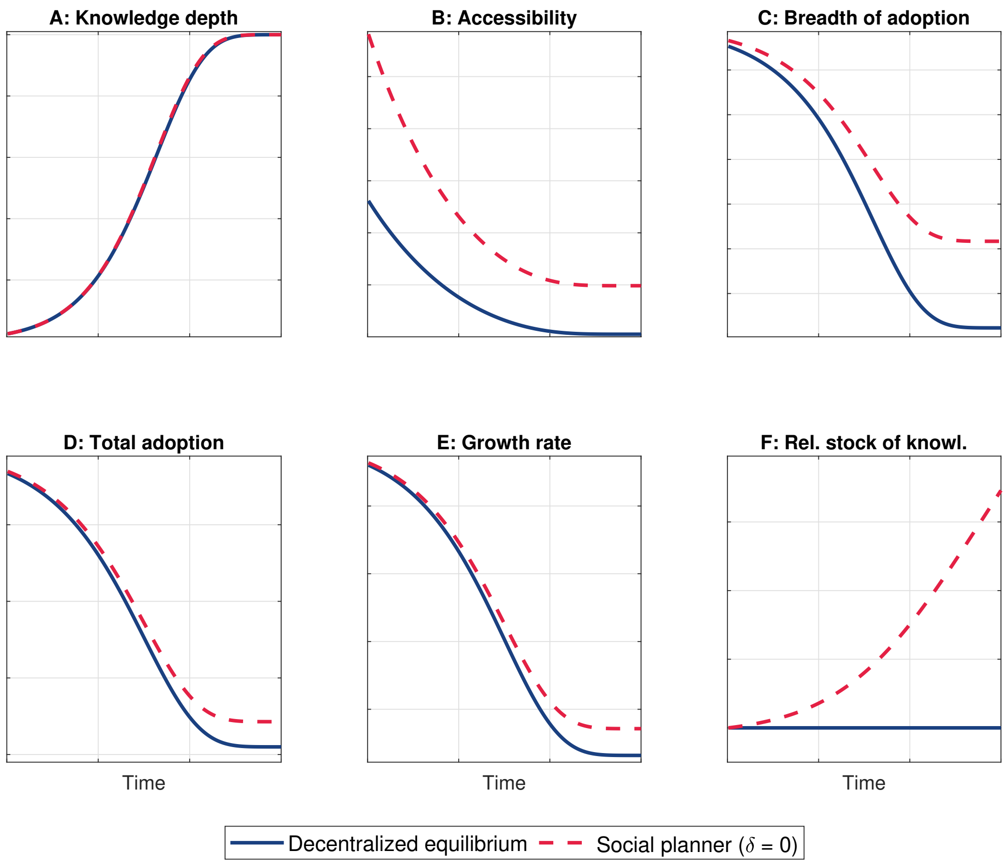
All other parameters are as defined in the static framework. The system $\{K_t, k_t, M_t\}$ fully characterizes the evolution of knowledge (and hence output) over time.

6.2 Dynamic paths and the role of policy

The model is deliberately stylized and is used to illustrate qualitative, rather than quantitative, implications of the theory. As long as the analytical restrictions derived in Section 2 hold and the empirically relevant case $\psi < 1$ is imposed, the dynamic predictions of the model do not depend on specific numerical parameter values. We therefore present the results abstracting from a particular calibration, focusing instead on trajectories that satisfy those restrictions and deliver interior solutions at all points in time.

Figure 11 displays the time paths of the endogenous variables. The solid blue lines correspond to the decentralized equilibrium, where scientists exhibit an own-field bias ($\delta > 0$). The dashed red lines correspond to the social planner solution ($\delta = 0$), in which communication choices fully internalize the social value of diffusion across fields.

Figure 11: **Dynamic paths of main variables**



Notes: The figure shows the dynamics of model variables under decentralized equilibrium (solid blue, $\delta > 0$) and social planner solution (dashed red, $\delta = 0$). As knowledge depth rises, the planner chooses higher language accessibility, resulting in greater total adoption, broader diffusion across fields, and higher growth rates.

As the stock of knowledge grows, the knowledge depth underlying new ideas rises monotonically (panel A). In response, scientists gradually reduce the accessibility of their language (panel B), reflecting the steepening of the tradeoff between precision for insiders and intelligibility for outsiders. Lower accessibility, in turn, narrows the breadth of diffusion across fields (panel C). These three dynamics mirror the main empirical patterns documented in the paper: ideas build on deeper layers of prior knowledge, are communicated in less accessible language, and diffuse across a narrower range of fields. As diffusion narrows, the overall adoption rate declines (panel D). Consequently, the growth rate of knowledge—and therefore of output—falls over time (panel E). The economy thus experiences an endogenous slowdown in scientific productivity: the frontier continues to expand, but each new idea contributes less to aggregate knowledge because it reaches fewer potential adopters.

A natural point of comparison is the case in which the own-field bias is eliminated ($\delta = 0$), which, in this framework, corresponds to the planner's solution. This environment can be interpreted as one in which institutions or policies succeed in aligning scientists' incentives with the social value of broad diffusion. When scientists place greater weight on the adoption of their ideas by other fields, they choose higher levels of accessibility, and diffusion remains substantially larger. As a result, the knowledge stock grows more quickly, and the economy converges to a balanced growth path with permanently higher growth rate and welfare, with the gap in accumulated knowledge relative to the decentralized equilibrium widening over time (panel F).

This simple setting illustrates how the interaction between rising knowledge depth and communication choices can generate a decline in the social value of new ideas and a gradual slowdown in productivity growth. It also shows how policy and institutional incentives that foster broad diffusion can mitigate these forces.

7 Discussion

The social returns to science can decline as a consequence of knowledge accumulation itself: as new ideas build on deeper layers of prior work, scientists respond by favoring more specialized language, widening the comprehension gap between their field and potential adopters. Ideas reach fewer fields, and a smaller share of their potential social value is realized. This mechanism operates independently of idea quality: a scientific frontier that continues to produce important discoveries will generate diminishing social returns if those discoveries become progressively harder to understand beyond a narrow audience. Our empirical results support this account. Over the past four decades, as the knowledge depth underlying new ideas has grown, scientific communication has become less accessible and diffusion across fields has narrowed. In line with the mechanism, ideas built on deeper knowledge are communicated in less accessible language, and less accessible ideas diffuse less widely.

These findings imply that policies that expand the knowledge frontier without addressing the forces that narrow diffusion may leave part of the social value of science unrealized. Recent work argues that sustaining the production of new science requires ever larger investments as ideas become harder to find. Our evidence suggests that narrowing diffusion exacerbates this challenge: even a constant flow of new ideas generates smaller aggregate returns when each idea reaches fewer potential applications.

Broadening diffusion requires adjustments to the incentives faced by scientists and research institutions. Existing structures mainly reward recognition from nearby peers: tenure decisions, peer review, and grant allocations are primarily designed to assess impact within a field. In our framework, these incentives affect communication because scientists rationally favor specialized language when institutional rewards are concentrated within their own field. This pushes accessibility below its socially optimal level and limits broader adoption. Realigning these incentives is thus central to widening diffusion. Funding agencies could place greater weight on influence beyond a project's field of origin. Universities could incorporate measures of reach across fields into promotion decisions. Journals could adopt editorial practices that reward accessibility alongside technical rigor. Each of these interventions would shift the tradeoff scientists face when communicating their work, encouraging choices that support wider adoption.

Investments in the infrastructure of scientific dissemination can complement these incentive changes. Science communicators who work to convey complex ideas to broader audiences are central to this process. As scientific work becomes more complex, making it accessible increasingly requires subject-matter knowledge together with the ability to communicate ideas clearly to audiences of non-specialists. This creates a growing role for dedicated expertise in scientific communication. New technologies, including large language models, may support research productivity by lowering the cost of translating complex ideas into forms that can be used without field-specific expertise.

The benefits of broader accessibility extend beyond adoption by other scientists. Clear, transparent, and accessible communication can strengthen public trust in scientific evidence, improve its use in applied innovation and policy design, and help inspire future generations of researchers. These broader effects point to promising avenues for future research on scientific communication and its implications for the social value of science.

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Online Appendix
(for online publication only)

The Decline in the Transmission of Scientific Ideas

by Enrico Berkes and Ruben Gaetani

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A Derivations

A.1 Derivation of Equation (10)

Consider the definition of total adoption in Equation (8):

$$M \equiv \int_0^1 \mu(i)\, \mathrm{d}i. \tag{A.1}$$

Multiplying and dividing the right-hand-side by $\mu(0)$:

$$M \equiv \mu(0) \int_0^1 \frac{\mu(i)}{\mu(0)}\, \mathrm{d}i. \tag{A.2}$$

Using the fact that $\mu(i) = \zeta - \lambda\, k^{\psi}\, a^{-\phi}\, i - \eta\, k\, a$, it is easy to show that

$$\int_0^1 \frac{\mu(i)}{\mu(0)}\, \mathrm{d}i = 1 - \frac{\lambda\, k^{\psi}\, a^{-\phi}}{2\,(\zeta - \eta\, k\, a)} \implies \frac{\lambda\, k^{\psi}\, a^{-\phi}}{\zeta - \eta\, k\, a} = 2 - 2\int_0^1 \frac{\mu(i)}{\mu(0)}\, \mathrm{d}i. \tag{A.3}$$

Using the same equilibrium function $\mu(i)$, we can express the breadth of adoption D as

$$D \equiv \frac{1}{M} \int_0^1 \mu(i)\; i\; \mathrm{d}i = \frac{\frac{1}{2} - \frac{\lambda\, k^{\psi}\, a^{-\phi}}{3(\zeta - \eta\, k\, a)}}{1 - \frac{\lambda\, k^{\psi}\, a^{-\phi}}{2(\zeta - \eta\, k\, a)}}. \tag{A.4}$$

Plugging Equation (A.3) into the last expression and rearranging yields

$$\int_0^1 \frac{\mu(i)}{\mu(0)}\, \mathrm{d}i = \frac{1}{4 - 6D}. \tag{A.5}$$

It is easy to show that, under our parameter restrictions, $D \in (\frac{1}{3}, \frac{1}{2})$ and, within this range, Equation (A.5) implies a monotonically increasing relation between D and $\int_0^1 \frac{\mu(i)}{\mu(0)}\, \mathrm{d}i$:[A.1]

$$\int_0^1 \frac{\mu(i)}{\mu(0)}\, \mathrm{d}i = \Theta(\underset{+}{D}),$$

[A.1] To see that $D \in (\frac{1}{3}, \frac{1}{2})$, note our parameter restrictions require $\mu(i) \in (0, 1)$ for all i, implying $0 < \frac{\lambda k^{\psi} a^{-\phi}}{\zeta - \eta k a} < 1$. Using Equation (A.4):

$$D - \frac{1}{3} = \frac{1 - \frac{\lambda k^{\psi} a^{-\phi}}{\zeta - \eta k a}}{6\left(1 - \frac{\lambda k^{\psi} a^{-\phi}}{2(\zeta - \eta k a)}\right)} > 0, \qquad \frac{1}{2} - D = \frac{\frac{\lambda k^{\psi} a^{-\phi}}{\zeta - \eta k a}}{12\left(1 - \frac{\lambda k^{\psi} a^{-\phi}}{2(\zeta - \eta k a)}\right)} > 0.$$

which, together with Equation (A.2), implies Equation (10).

A.2 Derivation of Insight 3

Insight 3 states that higher knowledge depth (k) lowers the breadth of adoption (D), and the decline is stronger when the researcher places more weight on nearby fields (i.e., when δ is higher or, equivalently, $\Omega(\delta)$ is lower). In other words, we will show:

$$\frac{\partial D}{\partial k} < 0 \qquad \text{and} \qquad \frac{\partial^2 D}{\partial k \, \partial \Omega(\delta)} > 0.$$

To show this, we start by using Equations (7) and (11) to express D as a function of exogenous variables and parameters only:

$$D = \frac{\frac{1}{2}\zeta - \frac{1}{3}\chi\tilde{k}\, s_1(\Omega) - \frac{1}{2}\chi\tilde{k}\, s_2(\Omega)}{\zeta - \frac{1}{2}\chi\tilde{k}\, s_1(\Omega) - \chi\tilde{k}\, s_2(\Omega)},$$

where

$$s_1(\Omega) \equiv (\phi\Omega)^{-\phi/(\phi+1)} \qquad s_2(\Omega) \equiv (\phi\Omega)^{1/(\phi+1)} \qquad \tilde{k} \equiv k^{\frac{\phi+\psi}{\phi+1}} \qquad \chi \equiv \lambda^{\frac{1}{\phi+1}}\, \eta^{\frac{\phi}{\phi+1}}.$$

Further define

$$P(\Omega) \equiv \chi\Big(\frac{1}{3}s_1(\Omega) + \frac{1}{2}s_2(\Omega)\Big), \qquad Q(\Omega) \equiv \chi\Big(\frac{1}{2}s_1(\Omega) + s_2(\Omega)\Big),$$

so that

$$D = \frac{\frac{1}{2}\zeta - P(\Omega)\tilde{k}}{\zeta - Q(\Omega)\tilde{k}}.$$

The restrictions we impose on the parameters are such that the denominator is always positive:

$$\zeta - Q(\Omega)\tilde{k} > 0.$$

Consider first the sign of $\partial D/\partial k$, which, given the definition of $\tilde{k}$, is the same as the sign of $\partial D/\partial \tilde{k}$. Differentiating D with respect to $\tilde{k}$ yields

$$\frac{\partial D}{\partial \tilde{k}} = \frac{-P(\Omega)(\zeta - Q(\Omega)\,\tilde{k}) - (\frac{1}{2}\zeta - P(\Omega)\,\tilde{k})(-Q(\Omega))}{(\zeta - Q(\Omega)\,\tilde{k})^2} = \frac{Q(\Omega)\,\frac{1}{2}\zeta - P(\Omega)\,\zeta}{(\zeta - Q(\Omega)\,\tilde{k})^2},$$

whose sign is equivalent to the sign of the numerator, $Q(\Omega)\,\frac{1}{2}\zeta - P(\Omega)\,\zeta$. It is easy to verify that this expression is always negative:

$$\frac{1}{2}Q(\Omega) - P(\Omega) = \chi\left(\frac{1}{4} - \frac{1}{3}\right) s_1(\Omega) < 0.$$

This proves that $\frac{\partial D}{\partial \tilde{k}} < 0$ and, as a result, $\frac{\partial D}{\partial k} < 0$.

Consider now the cross-derivative $\partial^2 D/(\partial \tilde{k}\,\partial\Omega(\delta))$, whose sign, given the definition of $\tilde{k}$, is the same as the sign of $\partial^2 D/(\partial k\,\partial\Omega(\delta))$. From the previous step we have the closed form

$$\frac{\partial D}{\partial \tilde{k}} = \frac{Q(\Omega)\,\frac{1}{2}\zeta - P(\Omega)\,\zeta}{(\zeta - Q(\Omega)\,\tilde{k})^2} = -\frac{\zeta\chi}{12}\,\frac{s_1(\Omega)}{(\zeta - Q(\Omega)\tilde{k})^2}.$$

Differentiating this expression with respect to Ω:

$$\begin{aligned}
\frac{\partial^2 D}{\partial\Omega\,\partial\tilde{k}} &= -\frac{\zeta\chi}{12}\,\frac{\partial}{\partial\Omega}\left[s_1(\Omega)\,(\zeta - Q(\Omega)\tilde{k})^{-2}\right] \\
&= -\frac{\zeta\chi}{12}\left[s_1'(\Omega)\,(\zeta - Q(\Omega)\tilde{k})^{-2} + s_1(\Omega)\cdot(-2)(\zeta - Q(\Omega)\tilde{k})^{-3}\cdot(-\tilde{k}\,Q'(\Omega))\right] \\
&= -\frac{\zeta\chi}{12}\,\frac{(\zeta - Q(\Omega)\tilde{k})\,s_1'(\Omega) + 2\tilde{k}\,s_1(\Omega)\,Q'(\Omega)}{(\zeta - Q(\Omega)\tilde{k})^3}.
\end{aligned}$$

Since $\zeta - Q(\Omega)\tilde{k} > 0$, the sign of the cross-partial is the opposite of the sign of

$$(\zeta - Q(\Omega)\tilde{k})\,s_1'(\Omega) + 2\tilde{k}\,s_1(\Omega)\,Q'(\Omega).$$

From the definition of $s_1(\Omega)$, it is trivial to show that $s_1'(\Omega) < 0$. We now show that $Q'(\Omega) < 0$ for $\Omega \in (0, 1/2)$ (the relevant range of Ω for $\delta > 0$), which, together with $s_1'(\Omega) < 0$ implies that the cross-partial derivative is positive. To show that $Q'(\Omega) < 0$, note that

$$Q(\Omega) \propto \frac{1}{2}(\phi\Omega)^{-\frac{\phi}{\phi+1}} + (\phi\Omega)^{\frac{1}{\phi+1}},$$

so that

$$Q'(\Omega) \propto \frac{1}{2}(-\frac{\phi}{\phi+1})(\phi\Omega)^{-\frac{\phi}{\phi+1}-1}\phi + \frac{1}{\phi+1}(\phi\Omega)^{\frac{1}{\phi+1}-1}\phi.$$

Simplifying this expression, it is easy to show that $Q'(\Omega)$ is always negative for $\Omega \in (0, \frac{1}{2})$, which is the relevant range for $\delta > 0$, proving the result.

B Details on the data and sample construction

Selection of articles. Some articles are written in other languages, but still provide an abstract in English. In this case, we include them in our final sample. We only consider breakthrough papers whose document type, as it appears in PubMed, falls within one of the following categories: "Journal Article," "Research Support, N.I.H., Intramural," "Research Support, Non-U.S. Gov't," "Research Support, U.S. Gov't, Non-P.H.S.," "Research Support, N.I.H., Extramural," "Research Support, U.S. Gov't, P.H.S.," "Multicenter Study," "Comparative Study," "Twin Study." In addition to these typologies of papers, when we identify adopting papers, we also consider the following types: "Randomized Controlled Trial," "Clinical Trial," "Clinical Trial, Phase I," "Clinical Trial, Phase II," "Clinical Trial, Phase III," "Clinical Trial, Phase IV," "Evaluation Studies," "Evaluation Study," "Pragmatic Clinical Trial," "Equivalence Trial," "Adaptive Clinical Trial," "Clinical Trial, Veterinary," "Observational Study, Veterinary," "Randomized Controlled Trial, Veterinary," "Validation Study," "Comparative Study."

Assigning a primary MeSH code to each concept. Our procedure to assign a primary MeSH code to each concept follows two main steps. In the first step, we propose a measure of similarity among MeSH codes that, in the second step, we combine with the observed distribution of MeSH codes for each concept to determine its primary code. The purpose is to identify the MeSH code that most closely reflects the concept's main topic area. For example, if a concept's papers are jointly assigned three codes in "Inorganic Chemicals" (D01), four in "Organic Chemicals" (D02), and five in "Education" (I02), we would like the primary code to reflect that the concept is more about chemistry than education.

Step 1: proximity between MeSH codes. We measure the proximity of two codes by how often a single researcher's recent work includes both. If a researcher publishes papers carrying two different codes, those codes plausibly capture knowledge that one person can understand and apply, and therefore are close to each other in the knowledge space. In other words, we want to capture the fact that codes describing related science tend to co-occur in researchers' portfolios more often than chance. For any pair of distinct codes (x, y), their proximity in year t is

$$\tilde{s}_t(x, y) \equiv \frac{P_t(x \cap y)}{P_t(x)\, P_t(y)}, \tag{B.6}$$

where $P_t(x \cap y)$ is the share of researchers active in year t who published in both x and y over the preceding ten years, and $P_t(x)$ (resp. $P_t(y)$) is the share who published in x (resp. y) over the same time window. The measure equals one when two codes appear in portfolios independently and exceeds one when they co-occur more often than chance predicts.[B.2] We recompute the similarity each year, since pairs of codes may converge or diverge as science evolves.

We bound this measure between 0 and 1 and set the similarity on the diagonal to 1. To do this, we apply the monotonic transformation

$$s_t(x,y) \equiv \begin{cases} \frac{2}{\pi} \arctan \tilde{s}_t(x,y), & x \neq y, \\ 1, & x = y, \end{cases} \tag{B.7}$$

which maps proximity into $[0,1)$ for distinct codes and sets the proximity of a code with itself to one.

Step 2: selecting the primary code. Let $n_c(x)$ denote the number of times code x is assigned across the breakthrough papers of concept c, pooled across those papers (a count, since first-level codes can repeat). Evaluating the proximity matrix in the concept's introduction year $\mathcal{T}(c)$, we select the code with the highest proximity-weighted prevalence:

$$\mathcal{M}(c) \;=\; \arg\max_{x} \sum_{y} s_{\mathcal{T}(c)}(x,y)\, n_c(y). \tag{B.8}$$

Since a code's own count enters with weight one, and related codes enter with positive weight, a cluster of related codes can outweigh a more frequent but isolated one. In the example above, this would translate into selecting chemistry as the concept's primary code.

[B.2] This is the role played by the denominator: when two codes are both fairly common in our sample, the fact that they often co-occur might simply be due to chance. Our measure normalizes the chance of seeing two codes together by how common each code is in the sample.

C Additional tables

Table C.1: **Most adopted concepts by decade**

Concept	Year first appearance	# Adopters (10 yrs.)
Decade: 1980-1989		
Immunodeficiency virus	1986	15,189
Reverse Transcriptase PCR	1989	12,585
Immunoblotting	1980	7,734
Decade: 1990-1999		
Chemokine	1992	7,313
Mitogen-activated protein kinase	1990	6,668
Leptin	1995	6,656
Decade: 2000-2009		
Exome sequencing	2008	7,773
Triple-negative breast cancer	2006	2,601
Drug-eluting stent	2001	2,214

Notes: The table reports, for each decade, the three newly introduced concepts with the highest number of adopting papers. Each concept is named using the most common wording with which it appears in the corpus. The number of adopters only includes adopters in the first ten years since the concept was first introduced.

Table C.2: **Language accessibility and breadth of adoption (computed using BioBERT) of newly introduced concepts**

	Adjusted breadth of adoption (BioBERT)		
	(1)	(2)	(3)
Language accessibility	0.229***	0.204***	0.162***
	(0.008)	(0.009)	(0.008)
N	39,807	39,807	39,268
R^2	0.073	0.088	0.190
# brkthr authors f.e.	✓	✓	✓
# brkthr × adopter papers cat.	✓	✓	✓
Primary MeSH f.e.	×	✓	×
Primary MeSH × Year f.e.	×	×	✓

Notes: Standard errors clustered at the year-primary MeSH level in parenthesis. $^{***}p < 0.01$.

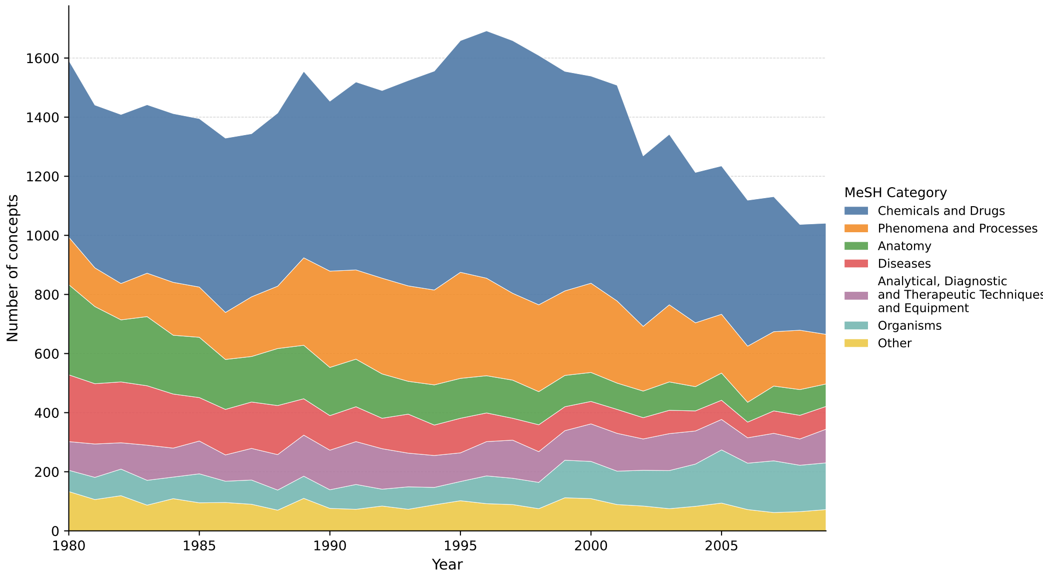
Table C.3: **Knowledge depth, language accessibility, and breadth of adoption (computed using BioBERT)**

	Adjusted breadth of adoption (BioBERT)					
	(1)	(2)	(3)	(4)	(5)	(6)
Knowledge depth	-0.059***	-0.045***	-0.046***	-0.046***	-0.037***	-0.033***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Language accessibility		0.225***		0.201***		0.160***
		(0.010)		(0.009)		(0.008)
N	39,807	39,807	39,807	39,807	39,268	39,268
R^2	0.047	0.075	0.070	0.090	0.155	0.166
# brkthr authors f.e.	✓	✓	✓	✓	✓	✓
# brkthr × adopt. p. cat.	✓	✓	✓	✓	✓	✓
Primary MeSH f.e.	×	×	✓	✓	×	×
Primary MeSH × Year f.e.	×	×	×	×	✓	✓

Notes: Standard errors clustered at the year-primary MeSH level in parenthesis. $^{***}p < 0.01$.

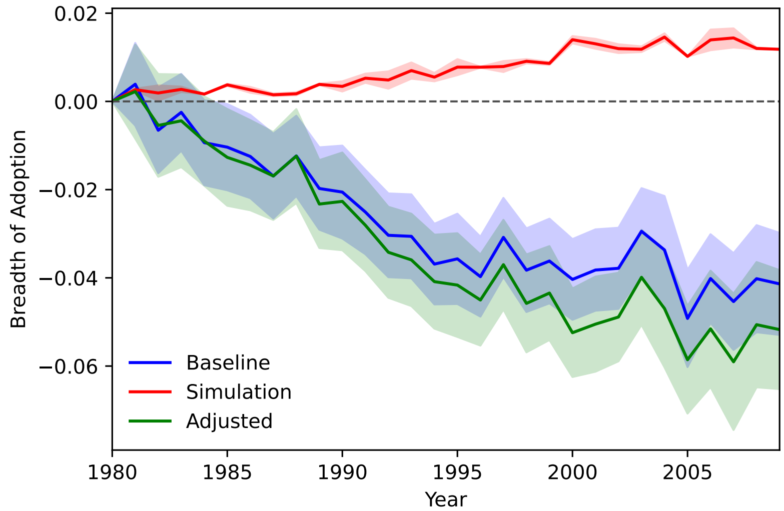
D Additional figures

Figure D.1: **New concepts by year and primary MeSH category, 1980-2009**



Notes: The figure shows the number of new concepts introduced each year, grouped by primary MeSH category. The sample is restricted to concepts included in the empirical analysis: those adopted by at least three papers within ten years of introduction.

Figure D.2: **Breadth of adoption of newly introduced concepts, computed using BioBERT: Data vs Simulations**



Notes: Semantic distance computed using embeddings from BioBERT (Lee et al., 2020). The blue and green lines plot point estimates and 95% confidence intervals of β_t from Equation (12). Blue line: the outcome is defined as D_c, i.e., the median of the pairwise cosine distances between the breakthrough and adopters of concept c ($R^2 = 0.065$). Green line: the outcome is defined as $\tilde{D}_c = D_c - \bar{D}_c$, that is, the difference between the median of the pairwise cosine distances between the breakthrough and adopters of concept c, and the corresponding average across 12 simulations ($R^2 = 0.087$). The red line plots the average point estimates of β_t from Equation (12) for the 12 simulations, together with the minimum and maximum estimate, where the outcome in each estimation s is defined as $\hat{D}_{c,s}$. Standard errors are clustered at the level of the concept's introduction year interacted with the primary MeSH code. $N = 42,470$.

E Illustrating the accessibility and distance measures

Figure E.1: **Abstract of Lemaitre et al. (1996).**

> Cell. 1996 Sep 20;86(6):973-83. doi: 10.1016/s0092-8674(00)80172-5.

The dorsoventral regulatory gene cassette spätzle/Toll/cactus controls the potent antifungal response in Drosophila adults

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Affiliations + expand

PMID: 8808632 DOI: 10.1016/s0092-8674(00)80172-5

Free article

Abstract

The cytokine-induced activation cascade of NF-kappaB in mammals and the activation of the morphogen dorsal in Drosophila embryos show striking structural and functional similarities (Toll/IL-1, Cactus/I-kappaB, and dorsal/NF-kappaB). Here we demonstrate that these parallels extend to the immune response of Drosophila. In particular, the intracellular components of the dorsoventral signaling pathway (except for dorsal) and the extracellular Toll ligand, spätzle, control expression of the antifungal peptide gene drosomycin in adults. We also show that mutations in the Toll signaling pathway dramatically reduce survival after fungal infection. Antibacterial genes are induced either by a distinct pathway involving the immune deficiency gene (imd) or by combined activation of both imd and dorsoventral pathways.

Notes: Taken from https://pubmed.ncbi.nlm.nih.gov/8808632/. Share of common words: 77.9%.

Figure E.2: **Prompt and abstract rewritten using accessible language**

Please rewrite the abstract below as a clear, plain-language scientific abstract for a broad, non-specialist audience. The reader may be a scientist from a different field, a policymaker, a journalist, or a generally educated reader with only basic scientific knowledge. Your main goal is to communicate the paper's central question, main finding, evidence, and significance as clearly as possible. Prioritize simple, direct communication over completeness. You may simplify, compress, or omit technical details when they are not essential to understanding the main message. Do not try to preserve the original wording, sentence structure, or level of detail. Avoid technical jargon as much as possible. When a technical term is not essential, replace it with plain language rather than using the term and then defining it. Use technical terms only when they are needed for scientific accuracy. The abstract should still be scientifically accurate and appropriate for an academic paper. Do not introduce claims that are unsupported, misleading, or overly broad. However, it is acceptable to sacrifice some precision and detail in order to make the main argument easier to understand. Keep the result as a single-paragraph abstract, roughly similar in length to the original, but make readability and comprehension the priority. Aim for the best balance between accessibility and rigor, without assuming that intelligibility to readers in the paper's own field or adjacent fields is more important than intelligibility to readers outside those fields. The abstract should not assume that the reader knows the field's standard concepts, methods, terminology, or motivation.

Fruit flies and mammals use surprisingly similar molecular systems to control both development and immune defense. This study shows that a signaling pathway first known for helping shape the early fruit fly embryo also helps adult flies fight fungal infection. We find that several components of this pathway, including the Toll receptor and its activating signal spätzle, are required to turn on drosomycin, a gene that produces an antifungal peptide. Flies with mutations in this pathway are much less likely to survive fungal infection, showing that the pathway has a real protective role. The study also shows that flies use different immune routes for different kinds of microbes: some antibacterial genes depend on a separate pathway controlled by the immune deficiency gene, while others require input from both pathways. These findings reveal that ancient immune signaling systems are shared across animals and that fruit flies can help explain basic principles of immune defense.

Notes: Prompt (left) used to generate the abstract (right), using Chat GPT 5.5. Share of common words: 92.7%.

Figure E.3: **Abstracts at different scientific distances from Lemaitre et al. (1996)**

Same narrowly defined area
Cosine distance: 0.334

› Science. 2006 Apr 21;312(5772):452-4. doi: 10.1126/science.1125694. Epub 2006 Mar 23.

RNA interference directs innate immunity against viruses in adult Drosophila

Xiao-Hong Wang [1], Roghiyh Aliyari, Wan-Xiang Li, Hong-Wei Li, Kevin Kim, Richard Carthew, Peter Atkinson, Shou-Wei Ding

Affiliations + expand

PMID: 16556799 PMCID: PMC1509097 DOI: 10.1126/science.1125694

Abstract

Innate immunity against bacterial and fungal pathogens is mediated by Toll and immune deficiency (Imd) pathways, but little is known about the antiviral response in Drosophila. Here, we demonstrate that an RNA interference pathway protects adult flies from infection by two evolutionarily diverse viruses. Our work also describes a molecular framework for the viral immunity, in which viral double-stranded RNA produced during infection acts as the pathogen trigger whereas Drosophila Dicer-2 and Argonaute-2 act as host sensor and effector, respectively. These findings establish a Drosophila model for studying the innate immunity against viruses in animals.

Same broadly defined area, different subfield
Cosine distance: 0.575

› Science. 2013 Aug 23;341(6148):903-6. doi: 10.1126/science.1240933. Epub 2013 Aug 8.

Cyclic GMP-AMP synthase is an innate immune sensor of HIV and other retroviruses

Daxing Gao [1], Jiaxi Wu, You-Tong Wu, Fenghe Du, Chukwuemika Aroh, Nan Yan, Lijun Sun, Zhijian J Chen

Affiliations + expand

PMID: 23929945 PMCID: PMC3860819 DOI: 10.1126/science.1240933

Abstract

Retroviruses, including HIV, can activate innate immune responses, but the host sensors for retroviruses are largely unknown. Here we show that HIV infection activates cyclic guanosine monophosphate-adenosine monophosphate (cGAMP) synthase (cGAS) to produce cGAMP, which binds to and activates the adaptor protein STING to induce type I interferons and other cytokines. Inhibitors of HIV reverse transcriptase, but not integrase, abrogated interferon-β induction by the virus, suggesting that the reverse-transcribed HIV DNA triggers the innate immune response. Knockout or knockdown of cGAS in mouse or human cell lines blocked cytokine induction by HIV, murine leukemia virus, and simian immunodeficiency virus. These results indicate that cGAS is an innate immune sensor of HIV and other retroviruses.

Unrelated area of biomedical research
Cosine distance: 0.738

› Science. 2000 Aug 4;289(5480):739-45. doi: 10.1126/science.289.5480.739.

Crystal structure of rhodopsin: A G protein-coupled receptor

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PMID: 10926528 DOI: 10.1126/science.289.5480.739

Abstract

Heterotrimeric guanine nucleotide-binding protein (G protein)-coupled receptors (GPCRs) respond to a variety of different external stimuli and activate G proteins. GPCRs share many structural features, including a bundle of seven transmembrane alpha helices connected by six loops of varying lengths. We determined the structure of rhodopsin from diffraction data extending to 2.8 angstroms resolution. The highly organized structure in the extracellular region, including a conserved disulfide bridge, forms a basis for the arrangement of the seven-helix transmembrane motif. The ground-state chromophore, 11-cis-retinal, holds the transmembrane region of the protein in the inactive conformation. Interactions of the chromophore with a cluster of key residues determine the wavelength of the maximum absorption. Changes in these interactions among rhodopsins facilitate color discrimination. Identification of a set of residues that mediate interactions between the transmembrane helices and the cytoplasmic surface, where G-protein activation occurs, also suggests a possible structural change upon photoactivation.

Notes: Top left: Wang et al. (2006); Top right: Gao et al. (2013); Bottom: Palczewski et al. (2000).

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