Rethinking Metrics

A Quick Guide to Questioning the Data That Drive Us

Tara McMullin, What Works

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introduction

We have access to more data about ourselves and the world around us than ever before.

On my morning run, I can check my current heart rate, monitor my pace, and check my mileage thanks to a tiny computer on my wrist. Then, I can pull up an app on my phone and check all of that data against yesterday's or last year's data.

I can visit a page on my website host to see how many people visited my last article or unsubscribed from my last email.

I could keep going, of course. But I won't. You know about all this data already. And whether you're the kind of person who obsesses over it or the type of person who ignores it completely (or any other kind of person in between), you know that the way we interact with data and the metrics we choose to follow impact us in profound ways.

That impact can be positive. But it can also be negative—even quite harmful and destructive.

The ubiquitous metrics and data that mediate our lives and work regularly lead us astray. Data appears to be an objective representation of reality. It seems to promise that if only we could fully grasp its secrets, we'd have the answers to all our questions.

When we look at our website analytics, the metrics on the last email broadcast we sent, or the insights on a social media post, are we really staring down the answer to the ultimate questions of life, the universe, and everything? It's a nice idea—that the perfect strategy is ours as soon as we unlock the cipher. A nice but false idea.

While our unprecedented access to data can help us learn about ourselves, our bodies, our businesses, and more, our data are not objective measures of reality. The numbers and shapes we see in any given dashboard present themselves as they do because a human decided to put them there. That human inevitably has different needs, values, and relationships with systems than we do. They have a set of assumptions about what our goals are and what information would be useful. All of these considerations influence the data we have access to.

Data mediate how we see the world, what we deem important, and how we choose our actions. But we don't see data as media. We see data as facts. Since we don't see data as media, we don't perceive how data mediate our relationship with the world. We don't see the power structures embedded within data media. We rarely bother to seek out the message in data media.

Data are never just data—they are the product of our fears, our hopes, our questions and curiosities. Data are nothing without a narrative to go with them.

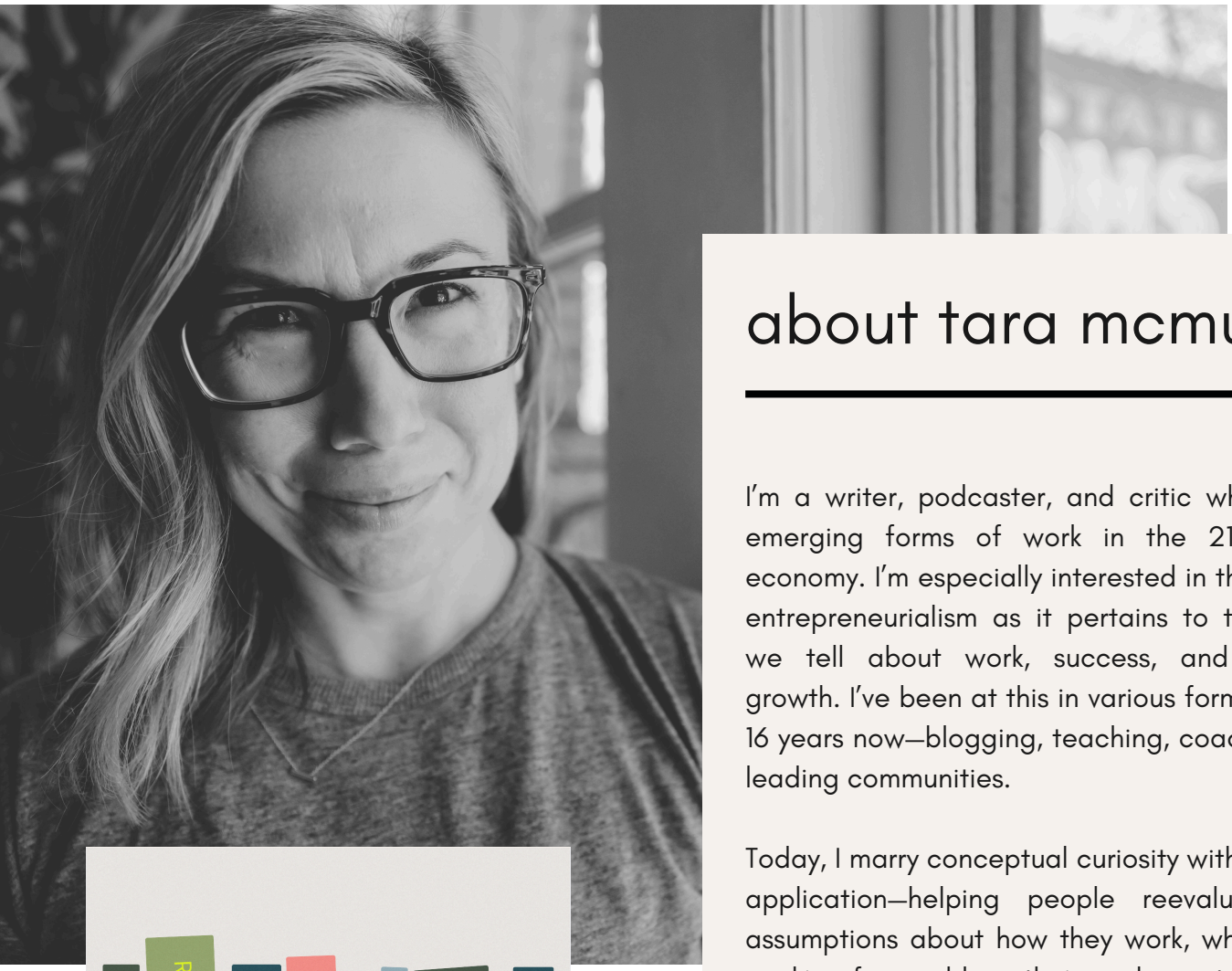
Data media shape how we think about the relationship between actions and goals. But data media can also shape our ideas of success, trigger anxiety, and lead us astray. The meaning of the data we pay attention to is always contingent, and it's up to us to make sense of that contingency. Because data mediate how we perceive and act on the world around us, we need a robust framework for interpreting and narrativizing data—especially when it comes to the metrics that are most visible and enticing.

This guide is a collection of previously published essays (2023-24) on rethinking metrics and data. They've been lightly revised and adapted to present a more or less cohesive framework for questioning our relationship with the numbers that seem inescapable today. It's not an argument for or against the use of metrics and data. Instead, it's a call for thoughtfulness, rigor, and a bit of healthy skepticism.

A Note About "Metrics" and "Data"

"Data" are information. They can be qualitative or quantitative. In this guide, I'll primarily be discussing quantitative data—information expressed in numbers of one sort or another.

"Metrics" are data that measures something—e.g., rate of change, number of events, percentage of an electorate, etc.



about tara mcmullin

I'm a writer, podcaster, and critic who studies emerging forms of work in the 21st-century economy. I'm especially interested in the spirit of entrepreneurialism as it pertains to the stories we tell about work, success, and personal growth. I've been at this in various forms for over 16 years now—blogging, teaching, coaching, and leading communities.

Today, I marry conceptual curiosity with practical application—helping people reevaluate their assumptions about how they work, what they're working for, and how their work creates value in the wider world. I draw on feminist analysis, critical theory, sociology, media studies, and philosophy, as well as my extensive experience working with small business owners.

I'm the creator of the *What Works* podcast and newsletter, as well as the author of *What Works: A Comprehensive Framework to Change the Way We Approach Goal-Setting* (Wiley 2022). My work has been featured on numerous podcasts, various stages, and in *Fast Company*, *The Muse*, and *Quartz*.

The Seduction of Clarity

metrics become incentives

Those incentives warp our choices and behavior.

The reason "what gets measured gets managed" is that moving the number in the desired direction becomes a reward in itself. We get that little dopamine rush from seeing the number tick up or down. And in the process, we tacitly endorse unhelpful and even harmful action for the sole purpose of seeing the number move.

Here's an example. Very early in my tenure as a podcaster, I learned that you could "double" the downloads your show received simply by releasing twice as many episodes. And you didn't even need to make more episodes! You could just take your back catalog and release one old episode along with your new one each week!

The reason this works (or was at least plausible) is that the bulk of a podcast's downloads come from subscribers. And typically, subscribers have episodes downloaded automatically to their devices. So whether they wanted to listen to the rerun episode or not, subscribers would find it on their devices.

A podcast might receive double the downloads, but this didn't actually mean that more people were listening to the show. It just meant that subscribers were leveraged to change a number.

I'm sorry to say that I was taken by this ridiculous scheme. I released a new episode every Tuesday and a rerun episode every Thursday. Initially, yes, my downloads went up—although they never doubled. But it didn't take long before this release schedule was pissing people off.

Now, there's nothing wrong with releasing reruns periodically. I've done it several times this year. But releasing them for the purpose of juicing your download numbers? That's ridiculous. I wish I could have seen that at the time, but I really wanted to increase my downloads even though I wasn't seeking outside advertising (the main reason you'd consider downloads as a metric in the first place). But that was just a downstream effect of how the scheme was invented in the first place.

Someone—I don't remember who—was so interested in boosting their downloads that they realized they could exploit a kind of loophole. They eked out a slight advantage by leveraging that automatic download loophole and doubled their downloads. Further, they exploited this idea to garner attention from people who, like me, also wanted to influence that magical number.

I'm sure the initial advantage didn't last long, however. And they were probably off to exploit another loophole for the purpose of juicing their numbers in short order.

This, by the way, is how much of late capitalist business growth happens.

A company identifies a slight advantage—often by playing fast and loose with metrics (e.g., page views, labor costs, cost of goods, etc). Then it jumps on that advantage and rides it for as long as possible—often just until the next earnings call. Then, it finds another slight advantage, and the process repeats.

This allows executives and shareholders to accumulate wealth while everyone else gets squeezed. The company doesn't work any better. It doesn't create more value outside of financial markets. It's just more successful on paper. The metrics that matter to investors become incentives to executives.

This isn't to say that making choices based on metrics always results in short-sighted behavior. But picking the wrong metric—the one that's not your real goal or one that you misunderstand the meaning of—will result in short-sighted behavior. The problem here is that most metrics, especially the highly visible ones, are the wrong metrics.

And if you operate at a scale that doesn't allow for meaningful data, well, then every quantifiable metric you have is the wrong metric. That is, unless you're dealing with numbers in the thousands, you probably don't have statistically significant data to make decisions with.

To use my cringy example from earlier, I allowed the number of downloads the podcast received to stand in for my goal of reaching more people. Building an audience and seeing higher download numbers aren't necessarily correlated—especially if you're looking at, say, monthly downloads rather than downloads per episode over time. I picked the wrong metric, imbued it with the character of an incentive, and then, rationally, chose the wrong tactic to move it.

I got the dopamine hit—
but very little else.

Okay, so when does a metric become an incentive? And how does a metric become an incentive?

I began to give these questions serious thought while listening to the sage of Sam Bankman-Fried, the criminally indicted (and now convicted) former CEO of crypto exchange FTX. SBF, as he's known, was also one of effective altruism's most prominent and financially generous supporters. There's reason to believe that SBF's desire to do good led him to make disastrously bad financial choices.

One theory of his destructive behavior is that he intended to make as much money as possible for the purpose of giving it away to projects that fell under the effective altruism banner. When he got way out over his skis with that scheme, everything collapsed. Innocent people lost money. And now that FTX is in bankruptcy, some of the money SBF gave away to researchers and charities may be clawed back to make investors whole.

What is effective altruism (EA)?

Effective altruism is a philanthropic philosophy that essentially prescribes giving money to projects that do the most good for the most people. The "most good" and "most people" are functions of metrics. Effective altruists use platforms like GiveWell and Giving What We Can to direct their giving based on the groups' research into the world's biggest—and most fixable—problems. Their goal is to maximize the impact of their dollars. There are plenty of big-name supporters of the EA movement—and there are also plenty of detractors and thoughtful criticism.

I won't get into that now (maybe in the future), but the idea that philanthropy can be measured objectively for the purpose of optimization and maximization is salient to our question about incentives.

Suppose you measure your positive impact on the world in terms of the number of mosquito nets distributed in sub-Saharan Africa. In that case, you're more likely to funnel as much money toward purchasing mosquito nets as possible. It feels good to have a direct impact on that data point. But if you measure your positive impact on the world through a set of subjective questions about the effects of your action on the well-being of people around the globe, well, you're going to have to do a lot of work. What's more, at the end of all that work to determine your impact, you won't have much confidence in your result.

Effective altruism is associated with another philanthropic scheme—earning to give. The idea is that it's preferable to choose careers that maximize earning and avoid jobs that, while beneficial or even "noble," don't pay as well. For instance, they might say that it's better for a lawyer to take a job in corporate law than to become a public defender. Sure, a public defender does work beneficial to the public. But the corporate lawyer might make orders of magnitude more money—which means they can give away more money to charities that benefit more people than a single public defender could ever help.

SBF figured out how to make a ton of money in crypto so that he could give it away. And he figured that he and his company would keep earning money to give away, which led him to rationalize giving away more money away than he actually had. This is no Robin Hood story. It's a story of misplaced incentives leading where misplaced incentives lead. SBF ostensibly believed that any negative impact of his earning actions were outweighed by the positive impact of his giving actions.

The clarity effective altruism provided incentivized harmful behavior.

Philosopher C. Thi Nguyen calls the flattening of a complex system of values "value capture." Value capture occurs when a nuanced understanding of what's important is squeezed into a simple data point.

One example Nguyen cites is GPA—grade point average. GPA is designed to objectively measure a student's performance and offer a way to compare one student's performance with another. Of course, student performance—let alone student learning—is a complex set of values. Different instructors will value performance in different ways—memorization, description, analysis, application, etc. Different students will perform differently depending on the learning context and performance measures. However, GPA turns all that complexity into a number between zero and four.

Students may then choose different strategies to boost their GPAs, such as taking easier classes or choosing instructors known to grade generously. Nuanced, complex ways of measuring performance are much harder to manipulate. But they also require many more resources to ascertain, record, and analyze. Moreover, simplified metrics like GPA provide what Nguyen calls the "seduction of clarity."

We get the feeling that we know exactly what's going on—even when we know no such thing.

As the world has gotten more and more complex, our opportunities to experience clarity have become more and more rare. That is if we're being honest about what we understand and what we don't understand. But, instead, we're constantly being seduced by the clarity of data: podcast downloads, inflation rate, page views, GDP, new subscribers, unemployment rate, post shares, housing prices, etc... Scroll past whatever political or tech scandal is the top headline, and you'll see a story about data.

I talk to vanishingly few people who don't get a little squirrelly about metrics. I regularly hear about projects gone wrong, vacations ruined, and harmful choices made, all in the name of improving some data point. Critic Rebecca Solnit calls our metrics-obsessed milieu the "tyranny of the quantifiable." Others have called it managerialism. Still others might offer slightly more holistic takes and call them "life hacking."

Nguyen's Theory of Value Capture

What we value is nuanced, contextual, and hard to measure.

Many contexts require simplified measures (often quantified) to ease tracking and comparison.

The simplified measures become the focus of our actions—rather than the value we originally (or nominally) hold.

> "The tyranny of the quantifiable is partly the failure of language and discourse to describe more complex, subtle, and fluid phenomena, as well as the failure of those who shape opinions and make decisions to understand and value these slipperier things. It is difficult, sometimes even impossible, to value what cannot be named or described, and so the task of naming and describing is an essential one in any revolt against the status quo of capitalism and consumerism." — Rebecca Solnit

It takes intention and sustainable effort to avoid the managerialist worldview. "Quantify everything" is a chief tenet of our faith in growth and progress. An effect that can't be measured isn't an effect at all. At the end of the day, we're trying to survive a system that grinds us down.

The best way forward may be one in which we refuse any quantification. I know that sounds drastic. And I'm not entirely sure that I mean it. But given our economy and culture, the siren song of data may be too seductive to deny unless we stuff our ears with wax or lash ourselves to the mast.

I have a hunch that we all know how to do good, effective work without relying on metrics to pat us on the back for a job well done.

Writing in The Atlantic, Derek Thompson wrestles with how to do the most good with his money. He writes:

Philosophically, the most difficult task facing GiveWell is putting the vast spectrum of human suffering into numbers. It is, in a way, a math problem, but one laden with value judgments, about which reasonable people can disagree.

For my money (pun intended), it's not a math problem. Nor is it a difficult task. Because human suffering and the many things that can and should be done to address it simply isn't a quantifiable issue.

We're all vulnerable to the seduction of clarity. It's nice to imagine that our trickiest problems—whether raising kids, running a business, or meeting fitness goals—can be reduced to an if this, then that line of code or even a multi-variable algebra equation. But relying on clarity when there is none is a formula for frustration and, often, harm.

The rest of this guide offers some concrete practices and frameworks you can use to sit with uncertain information, examine what you know (and what you don't), and move forward with strategic action.

Value Capture

"Value capture occurs when our values undergo a long-term and enduring simplification, as guided by the external metrics provided by institutions and technologies." —C Thi Nguyen

What we value is nuanced, contextual, and hard to measure.

Many contexts require simplified measures (often quantified) to ease tracking and comparison.

The simplified measures become the focus of our actions—rather than the value we originally (or nominally) hold.

1 What metric is influencing your action?

2 What does this metric claim to measure?

3 What does it actually measure?

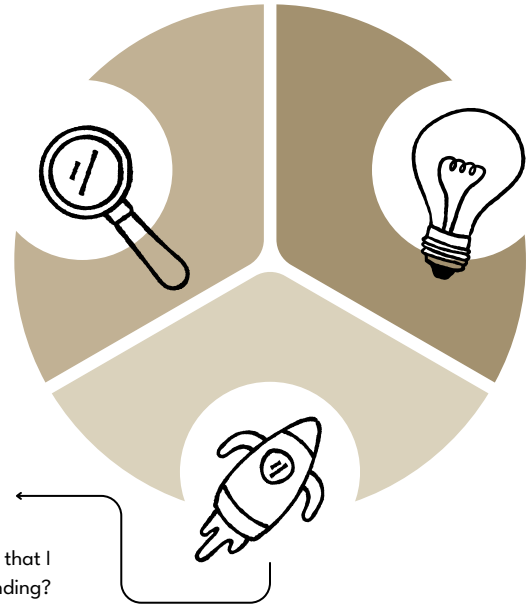
4 How does this metric align with a meaningful value?

5 How might you assess that value while retaining more of its richness?

3 Ways to Question Data

Predictability

Does this data reliably predict whether or not I'll achieve my desired outcome?



Relevance

Is this data closely connected to my desired outcome without unnecessary variables?

Actionability

Does this data create a pattern that I can act on to test my understanding?

1. predictability

One place to start examining the contingent meaning of data is to look at leading versus lagging indicators.

The vast majority of the goals we care most about—things like having a positive impact on clients or operationalizing our values—aren't quantitatively measurable. These goals are too complex and nuanced to be reduced to a single data point. However, data do help us discern patterns and judge future outcomes.

So, we feel around for things that are quantitively measurable and related to our most important goals. Often, these measurements help us predict what's going to happen and behave accordingly, or they help us take stock of what's already occurred and analyze it. Predictive metrics are leading indicators. Metrics that tell us what's already happened are lagging indicators.

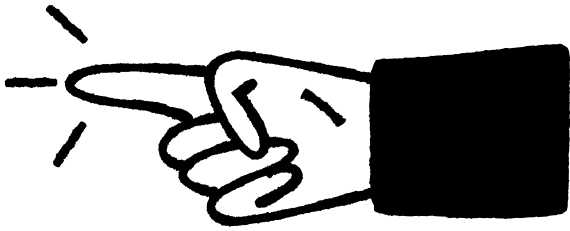
Ideally, leading indicators are closely tied to our goals, with enough wiggle room to make adjustments if they aren't leading us where we want to go. Lagging indicators often represent aspects of our goals without accounting for their full depth and breadth. Whether a particular metric is a leading or lagging indicator depends on the goal we're trying to apply it to.

Of course, some metrics are just junk. National polling for the U.S. presidential election is a metric that only matters to the media. The national popular vote has zero bearing on who becomes the president. National polling only matters in the sense that it helps the media make headlines, which create narratives, which form expectations, which impact behavior. National polls are metrics, but they aren't indicative of material results.

Because leading indicators allow us to adjust behavior when we're not making the progress we want to make, it's critical that we only give leading indicator status to metrics that have a bearing on outcomes. It's also critical that we pay attention to the right outcomes—often easier said than done. National polling seems like it should be a leading indicator given the way the media covers it. It feels important. So we start to give national polling leading indicator status and, in doing so, give the status of the desired outcome to winning the popular vote. But if that's the focus of a campaign strategy, that campaign may very well lose.

Keeping your eye on the prize might seem like a no-brainer. However, the way we process metrics and data can often lead us to focus on outcomes we have no interest in outside of their relationship with easily trackable metrics. We substitute visible metrics for ones that are more closely related to our goal—and therefore offer a higher potential for predicting our chances of success.

Predictability hinges on the distance between the data and the desired outcome.



Many years ago, a coach encouraged me to consider my 'earnings per lead' as a way of thinking about how to hit my revenue target. Revenue is a lagging indicator, of course. Once I knew my revenue for a period, I couldn't do anything to change it. But thinking about revenue (i.e., earnings) in relation to leads (in this case, email subscribers) could—in theory—help me make decisions about growing my audience and selling offers.

Leads—as one expects—are typically leading indicators. For the uninitiated, a 'lead' means a potential customer or client by virtue of some action they've taken. Some leads carry more meaning than others. A 'hot lead' might be someone who has verbally committed to working with me or signed up for an initial consultation. A cooler lead is someone who has expressed interest (e.g., attended a webinar or signed up for an email list) but isn't on the verge of buying yet.

By measuring 'earnings per lead' (EPL) in relation to my email list as a whole, I created an unrealistically close connection between email subscribers and clients. I assumed that the leads would turn into sales at about the same rate as before. But rapid growth (or rather, what we do to achieve rapid growth) often dramatically changes this rate. The actions I took to grow the number of leads led to a precipitous decline in the rate at which leads turned into sales.

I ignored the contingency embedded in this metric—the fact that my EPL would change as my strategy changed, that the relationship between my email list and my ability to predict how many people would buy was borked. I couldn't assume that my EPL would remain stable as my list grew—but I did. For my EPL to stay consistent, I needed to bring in leads of the same quality I had attracted before. Unfortunately, my assumptions made that nearly impossible.

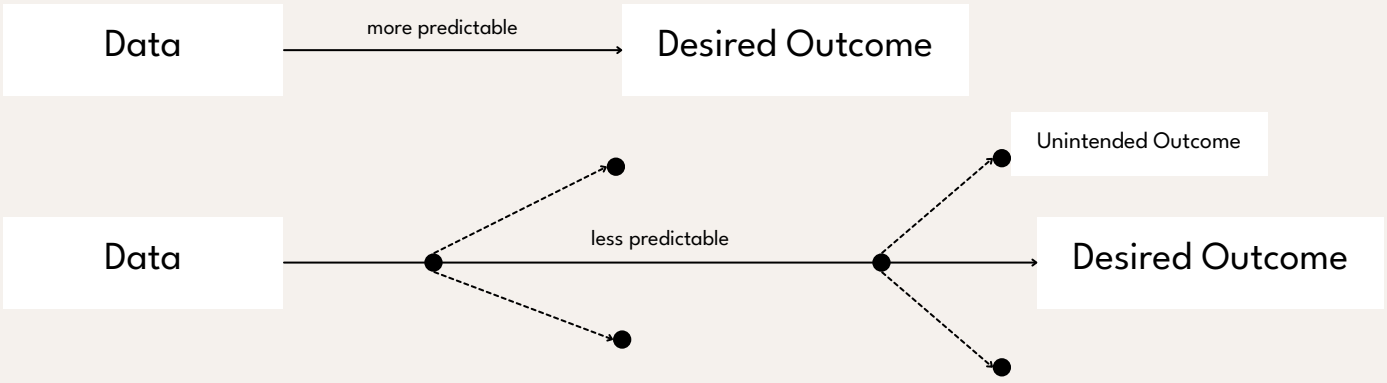
How I used the data mediated my approach to list-building and attracting leads. Because the number of leads seemed to be the leading indicator of progress toward my revenue target, I began to focus on generating more leads rather than attracting quality leads. The quantity of leads quickly superseded my revenue target as the desired outcome. Instead of working to increase leads in a way that would lead to my revenue target, I worked to increase leads full-stop.

In this, I was pretty successful. My email list grew and grew. My revenue did not.

'Earnings per lead' is a valuable metric. But only if it's utilized to understand the quality of your leads and the value of your offers. If you use it to inspire a focus on the quantity of leads, it's all but meaningless.

Predictability

Predictability hinges on the distance between the data and the desired outcome.



It's important to note that predictability does not mean causation. A metric can help us predict outcomes without the subject it measures causing the outcome we're looking for.

2. relevance

Predictive relationships between data & outcomes aren't always relevant to our goals.

Leading indicators are correlated to desired outcomes. Correlations aren't necessarily relevant, however.

Again, consider national polling in a presidential election. Before the 2000 U.S. election, national polling was consistently correlated to the outcome. No candidate who won the popular vote failed to win the Electoral College vote between 1888 and 1999. But it has happened twice since—in 2000 and 2016. While it seemed like national polls were relevant because they had been correlated, the two most shocking US elections of the 21st century reminded us that national polls are not relevant, even if they are correlated.

Similarly, at one time, the number of leads I attracted was positively correlated and highly relevant to my revenue. Once I started focusing on quantity over quality, though, the correlation remained, but its overall relevance plummeted. Sure, more leads would result in more revenue, but the relationship was no longer stable. I had less and less confidence in it.

Relevance is a product of the number of variables in the relationship between a leading indicator and a desired outcome. The further the distance between the leading indicator and the desired outcome, the more variables are bound to be present. The more variables there are, the less an indicator should be considered predictive—in other words, the more variables there are, the less likely a metric is to be a leading indicator at all.

The greater the distance between the data and the goal, the less relevant that data will be.

When I focused on the quantity of leads rather than the quality of leads, I widened the distance between my leading indicator and my desired outcome. I could achieve a quantity of leads by offering free events and downloads that I knew people were likely to take advantage of. Without ensuring that those events and downloads were targeted at highly motivated potential buyers, I introduced a host of new variables: urgency, readiness, pain points, goals, etc. What was once a straight line between leads and buyers became a wiggly, broken, unpredictable line.

Data mediate how we perceive reality and what we believe to be true.

None of my list-building tactics were nefarious. They just weren't very strategic. My failure to hit my revenue target that year, despite strong email list growth, was my own fault. My coach didn't tell me to pursue quantity over quality. There weren't any user interfaces unduly influencing my tactics. I just messed up because I forgot to prioritize the relevance of my data to my desired outcomes.

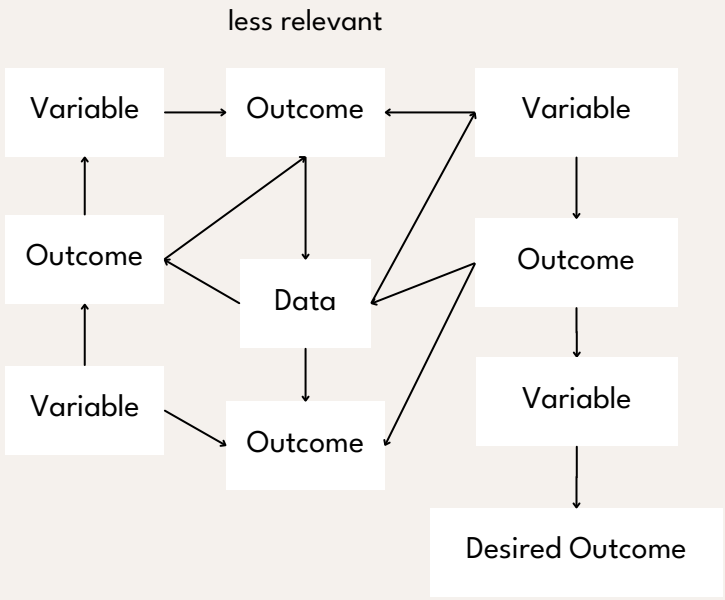
As I mentioned, this was a long time ago—almost a decade. Things have changed quite a bit since then. Today, platforms and apps love to help us track our metrics without regard to their relevance or connection to our desired outcomes. When I log into my podcast host, I'm presented with a 7-day chart of downloads. When I used to log into Substack, the metrics I saw are more relevant, but they're still predicated on Substack assuming my desired outcomes. My "professional dashboard" on Instagram offers "insights" such as views, interactions, and followers—none of which have any bearing on my desired outcomes.

These dashboards are a prime way that data mediate our perception of reality.

Data as media shape how we perceive the relevance of metrics like podcast downloads, Substack subscribers, and views of Instagram posts. Data as media hide—intentionally or not—the variables that inevitably complicate the information available. Data as media draw the curtain between strategic action and the people who choose what metrics influence that action.

Relevance

Data as media hide (intentionally or not) the variables that inevitably complicate the information available.



3. actionability

Just because we have a data point doesn't mean we can (or should) do anything with it.

Let's look at presidential polling one more time. Just a couple of weeks before the 2024 election, *The New York Times* released a poll showing Vice President Harris up 50%-46% over Trump in Pennsylvania, where I live. This poll result was an outlier—both from other PA polling and from national polling. If one were to view this poll in isolation, the data might suggest that PA was in the bag. The Harris campaign might decide to pull ad spending and put it into a state where the margin was closer.

Of course, the Harris campaign didn't do that because an outlier result isn't an actionable data point. That doesn't mean it's wrong; it means it's not useful. (Spoiler: it was very, very wrong.)

For data to be actionable, it must be supported by a pattern. Patterns further mediate data and illuminate the relationship between data and our desired outcome over time. Without a pattern, there are too many variables and too little predictability to make informed decisions about what to do next.

When data forms a pattern, we have a theory—a narrative—we can test based on our next actions. If we can influence the pattern, then we know how our actions relate to the data and have further proof of our theory. If we can't influence the pattern, we must rethink our theory.

In my 'earnings per lead' example, I didn't have a pattern. I had a single data point—my previous year's revenue divided by the number of people on my email list. If I'd looked at my EPL for previous years, my guess is that it would have been higher. I might have discovered that the pattern was a downward trend. Instead of focusing on growing my list, I might have asked myself how I could improve the quality of my leads or make offers better suited to the people on my list.

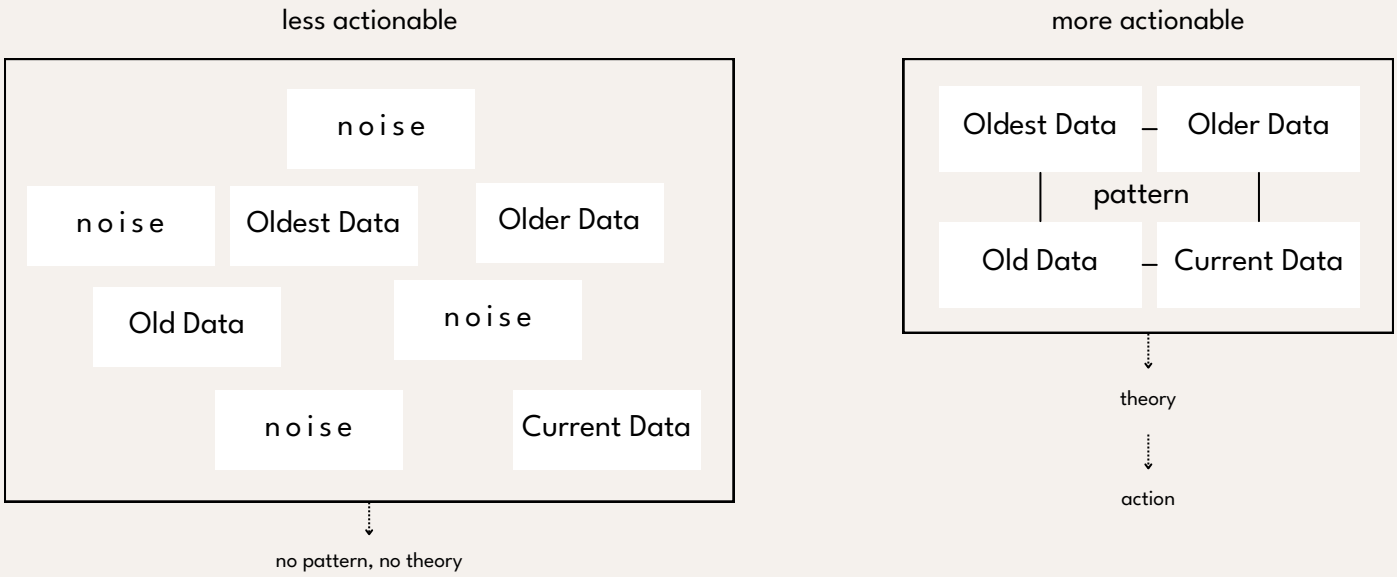
Instead, I took action on the single data point and, by the end of the year, wondered how things had gone so wrong.

Patterns are powerful tools for navigating the distance between data and a goal.

Patterns help us understand the contingencies embedded in our data, and they also help us draw closer, more direct connections between data and our goals. A pattern might not shrink the distance, but it will make the trip easier to navigate.

Actionability

When data forms a pattern, we have a theory (or narrative) we can test based on our next actions.



The Case for Data Literacy

Much has been said about the necessity of media literacy in the age of truthiness and fake news. We need to learn how media can be manipulated and trust can be misplaced. We must all consume news and other information responsibly if we're to maintain a functioning democracy and economy.

Similarly, systems literacy is critical for understanding the relationships between people, resources, and ideas. The more we attune our senses to perceive how systems reinforce each other, the more effective we'll be at catalyzing change and resisting the status quo.

We also need data literacy. That doesn't mean knowing how to read a spreadsheet or run the crosstabs on a research survey—although both are helpful. Data literacy requires us to acknowledge that the numbers don't speak for themselves, that statistics lie all the time, and that just because you can measure something doesn't mean it should be managed.

There's more to data literacy than what I've outlined here. But beginning with a critical framework of predictability, relevance, and actionability is a good place to start. Adopting this framework will help us make smarter decisions and take more strategic action all while allowing us to ignore the data that are just distractions and nothing more.

Questioning Data

Is is predictive?

1 How does this data point relate to my goal?

2 How closely are the data point and my goal related?

Is it relevant?

3 What variables are hiding to see when focusing on this data point?

4 How do those variables affect the relationship between this data point and my goal?

Is it actionable?

5 What's my theory for the pattern I see in this data (as it relates to my goal)?

4 What action can I take to test this theory?

The Subversive Potential of Defining Good

Abby Covert, *How to Make Sense of Any Mess*

"What we intend to do determines how we define words like good and bad."

The Good Filter

We have a myriad of ways to measure the results of our work.

Unfortunately, the vast majority have nothing to do with what we actually want to accomplish with our work.

When I'm not writing or podcasting myself, I'm an audio and video producer at YellowHouse.Media, the production studio I co-founded with my husband, Sean. The job of producer can mean many things, but my chief role is helping our clients think intentionally and strategically about the media they're creating.

To do that, the first thing I want to know about a new client is how they define a "good" outcome for the project we're working on. Not explicitly, but indirectly: What would success look like to you? What are your goals for this project? What are you hoping to accomplish?

No one answers with a number of downloads or views, and very few answer with the name of a blockbuster guest. Most describe a mix of emotions, creative challenges, and the odd business goal or two.

I need to know how they define good so that I can both steer them in that direction and remind them of what good means to them when they (almost) inevitably start to worry about the guests they're booking, the number of listeners they have, or the messages they haven't received from fans.

Because podcasting is built on old technology (RSS), we don't have access to the metrics we've become familiar with thanks to website analytics, video metrics, social media stats, etc. What metrics we have are unreliable at best. Defining what's good outside of seemingly clear-cut metrics is critical to understanding the performance of any given show as producers. It's also essential to a host's confidence and sense of self-efficacy.

Defining good gives us a filter for making decisions, including decisions about metrics and data.

I learned the importance of defining good from Abby Covert's *How to Make Sense of Any Mess*. It's a book about information architecture and sensemaking—which means it's really a book about how to approach anything and everything with intention.

Defining good allows us to collaborate better. When I know what good means to you, I can support you in a way that aims to make good a reality, which might be different from the way I support someone else who has their own definition of good.

Defining good gives us a handy framework for decision-making. While the best choice might appear unclear on the surface, our definition of good can help us choose the option that's a clear winner for us.

Defining good helps us rule out otherwise attractive possibilities. Saying 'yes' is often much easier than saying 'no.' And that means we can end up stretched thin and overcommitted. By defining good, we also define bad or not important when it comes to a particular project or even our work overall.

But I think the real magic of defining good comes in its ability to subvert assumptions. When we define good for ourselves, we don't need to rely on what's considered good in dominant ideology.

Dominant ideology becomes dominant by influencing what we perceive as good and bad. And often by imposing definitions of good and bad on groups of people that a dominant group wants to subjugate.

Productivity culture—an offshoot of managerialism—influences how we perceive what constitutes a good day's work. A good day's work is one that produces as much as possible. Therefore, a day spent coaching an employee or thoughtfully updating an online course likely registers as unproductive—or bad.

Neoliberal ideology influences how we perceive the role of higher education. It's good if it helps young adults get jobs, but it's bad if it empowers them to contextualize current events and protest injustice.

Supremacy culture influences how we perceive the moral value of certain types of behavior. We learn that disagreements are bad while appeasing the higher-ups is good. We learn that objectivity is good and relativity is bad.

How we define good as a society is a critical political question—perhaps, the critical political question.

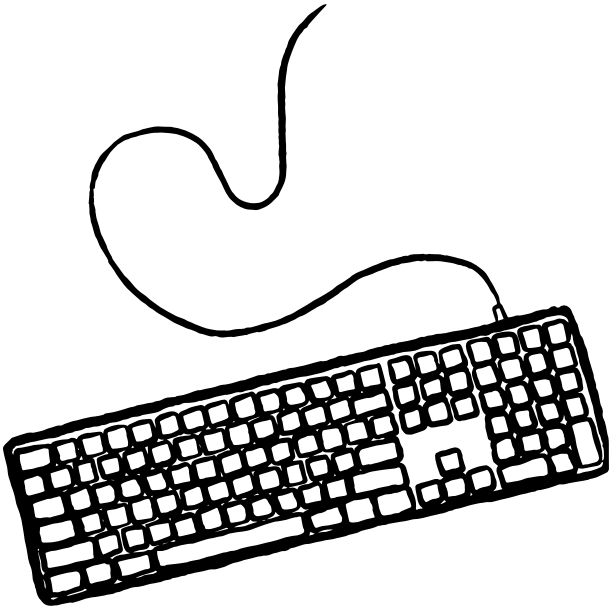
“The words we choose matter.”

How we define good as business owners, independent workers, and working people generally is critical to subverting business-as-usual practices. If we don't define good as constant growth, we can choose practices that prioritize maintenance and sustainability. If we don't define good as soaring profit margins, we can make organizational choices that care for team members and customers alike.

Or, to return to the podcasting example, if I don't define good as a number of downloads or a blockbuster guest, I'm free to define good as consistency, quality, or intellectual rigor.

"The words we choose matter," writes Covert, "They represent the ideas we want to bring into the world." If we're not careful about the words we choose, we reinforce preexisting ideas about the world. But when we're clear about our intent and make our definition of good explicit, we can bring ideas into the world that subvert the status quo.

And while our individual definitions of what's good won't shift ideology at a societal level, taking care to define what's good for ourselves helps us see ways we can redefine what's good with others at scale. It's a small and doable step that's critical to introducing more sustainable, compassionate, and human-centered modes of exchange into our communities.



Defining Good

Consider a project you're currently working on.

1 How will you know when this project is complete?

2 What words or concepts would describe a "good" result for the completed project?

3 What are words or concepts that others would value in the completion of this project that you're uninterested in or avoiding?

4 How could your project turn out differently from what you imagine but still result in a "good" outcome?

Making Sense of Data

Time, Practice, Repetition

The 2024 Summer Olympics Women's High Jump finals were a study in personal ritual.

Each jumper had her own way of centering herself, psyching herself up, and beginning her jump.

One of the Australian jumpers, Eleanor Patterson, began each jump with a slow shoulder shimmy that looked more like she was finding her groove on the dance floor than preparing to launch her body 6 feet in the air. The gold medalist from Ukraine, Yaroslava Mahuchikh, saved the most visible part of her personal ritual for between jumps. After getting up off the pads, she climbed into a thick sleeping bag to keep her muscles warm. Other jumpers slapped their thighs, closed their eyes, or let out a primal scream.

Australian Nicola Olyslagers, who was never seen without a huge smile on her face, looked to the crowd for support before yelling, "Let's go!" to begin her jump. Even when she missed, she sprang up off the pads, looking like she was having the time of her life. But it was what she did next that caught my (and many others) attention.

Olyslagers bounded over to the bench after each jump to record the attempt in her journal. She told ABC Sport that keeping a training log is "athletics 101." But what she's found especially valuable is reflecting on "what did I learn, what went well, and what do I need to change." Recalling the 2021 Olympics in Tokyo, she added that those reflections turned into inspiration she could take onto the track with her for the event—like she'd written herself notes for the big day months, or even years, in the past.

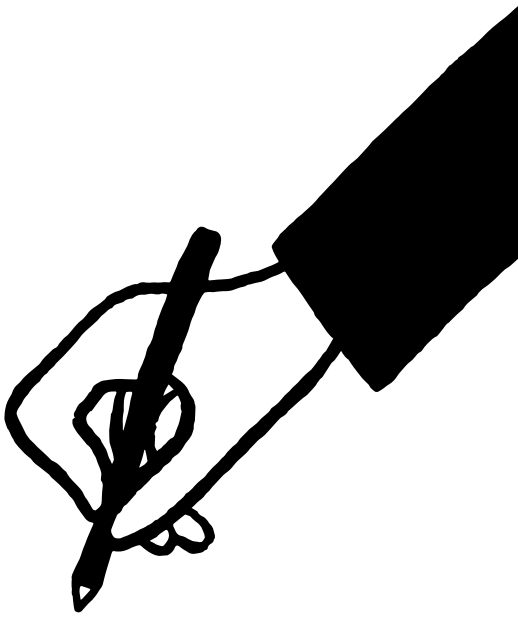
Elite athletes have access to sophisticated equipment that can quantify every aspect of their performance. If you've watched diving or gymnastics during this year's Games, you've probably seen the replays that snapshot a dive or a tumbling pass split second by split second. The amount of data that even casual athletes like myself have access to via our wearables is mind-boggling.

But data is just data until we make sense of it—make it mean something.

That's what Olyslagers does when she records her jumps in her journal and reviews her past performances. She makes sense of what went into each good attempt and what went wrong in failed attempts. The data is there, but she has to make it meaningful.

Work today revolves around data. From retail to hospitality, technology to construction, consulting to marketing, and advocacy to politics, our work is saturated with quantification. I've written about the ways this information can lead us astray before—how we become seduced by the *prospect of certainty* and how complex values are reduced to metrics. But data isn't bad; we don't need to avoid data as long as we're conscientious about how we interpret it.

Nicola Olyslagers's journal practice has (at least) three lessons we can all learn from.



1. Interpretation Takes Time

Olyslagers has been keeping her training journal for years. Heck, it's been to the Olympics twice. No single jump or even a series of jumps in a single event can tell her much. However, reviewing and contextualizing her performances over time allows her to see meaningful patterns and offer herself useful recommendations.

Too often, we want to know what a particular dip in performance means or what to make of this specific standout success. However, these data points don't mean anything on their own. They only mean something relative to other data points—both quantitative and qualitative.

How long does it take to get meaningful data? Well, that depends on what kind of meaning we're looking to make and what kind of data we're dealing with. What might be "statistically significant" for Olyslagers won't be statistically significant for another elite high-jumper. What's statistically significant for me won't be statistically significant for you.

Trying to make sense of single data points will inevitably lead to reactionary choices. We'll adjust things that don't need to be adjusted or abandon tactics that don't need to be abandoned.

Time is one of the great contextualizers. Data needs history to make it useful.

2. Making Sense is a Practice

Even once Olyslagers's silver medal was guaranteed, she kept recording her jumps—her commitment to the practice is essential to her performance.

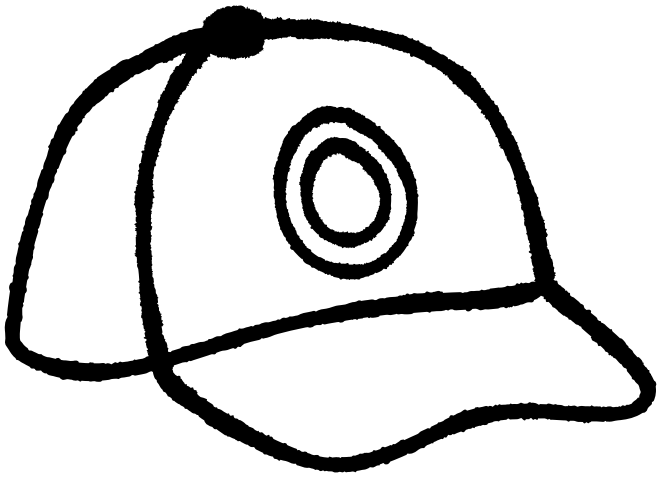
While I don't want to suggest that making sense of data requires obsessive attention to detail, it does require commitment and habit formation. Whether or not that habit is externalized in the form of a journal or spreadsheet or dashboard, it's the process that allows meaning to emerge from data.

Again, collecting data is easy—so easy you don't even have to think about it—it's just there. However, processing the data and turning it into an idea or a trend takes effort. Luckily, we already have a baseline for that effort. We process data every time we have a conversation with a partner or friend about how our day was. We process data when we tell our doctor or therapist what's been troubling us. We process data when we listen to our kid relate a story from school and ask for some advice.

We just don't often extend that practice to the data we use at work. Whether it's page views, podcast downloads, newsletter subscribers, conversion rates, or sales, I've noticed that we try to let those numbers stand on their own.

I've been asked many times whether a conversion rate of 3% (or 1% or 12%) is good. Well, good compared to what? How is that conversion happening? Who is in your sample? While I rarely get questions about conversion rates anymore, I still get plenty of questions about podcast downloads. What's a good number of downloads to shoot for? Absolutely no idea. I work on podcasts that receive tens of thousands of downloads per episode and podcasts that receive tens of downloads per episode.

As I mentioned earlier in this guide, “good” must be defined and a pattern must be established to make data make sense. Even what constitutes “good” and how a pattern is interpreted will change over time. By sticking with the practice of making sense of our metrics, we learn to take a longer view—one that’s less likely to lead to reactionary or urgent decision-making.



3. Act and Observe Again

We can't make sense of data if we don't act on what we think it indicates. Karl Wieck, the organizational psychologist who first described the sensemaking process, and his co-authors Kathleen Sutcliffe and David Obstfeld put it this way:

If the first question of sensemaking is "what's going on here?," the second, equally important question is "what do I do next?"

Making sense of data involves taking a stab at what's going on. For Olyslangers, that might mean guessing that her stride is a bit off or that her takeoff hasn't been as powerful as it needs to be. With that information in hand, she can go into the next jump and make a change based on that guess. After that jump, she observes again.
For a marketer, that might mean examining email list growth and guessing that sending fewer emails caused the dip they're observing. To test that presumption, they spend the next couple of months back on their old cadence—and observe again.

For an educator, this might mean observing that participants often get stuck at a certain point in a course and guessing that there's something that's not working in the curriculum design. To test that presumption, they adjust the curriculum to better guide participants through that common snag—and observe again.

For a journalist, this might mean observing a trend emerging on their beat and coming up with a theory for why that trend is happening. To test that presumption, they interview both experts and people participating in the trend to see if they're on the right track. From there, they might write up their article, or they might do more reporting to get even clearer on what's happening.

It can be difficult to know whether a noticeable change in a metric is relevant or a theory about the data in question is actionable. To figure it out, we have to act. Our capacity to use the data we have is contingent on our ability to observe changes based on our actions.

Our job is to develop ever-better frameworks for making sense of the data we have.

Many of us look at a pile of data and wish we had the exact layout, app, or algorithm to make sense of it. Data seem to represent facts that, when arranged properly, deliver objective answers to our questions. However, no algorithm could use all the data Olyslagers has captured over the years to discover the perfect formula for her next jump. There is, in fact, no perfect formula to discover.

Instead, her regular interaction with the data produces a mental framework she can use to adjust her form or try new things. She not only produces that mental framework but also becomes aware of it and improves it as she trains. She expands her idea of what's possible, likely, or effective based on how her framework shifts with new questions.

We use frameworks to navigate uncertainty and explore new domains of knowledge. "We might think that we are dealing with a familiar kind of problem, only to discover that we need to reconfigure our approach as we go along," writes philosopher Céline Henne. "Frameworks are crystallisations of our understanding of the world, and they remain transparent most of the time. We see through them instead of looking at them." But when we do practice engaging with those frameworks—when we pay attention to how we're thinking and not only what we're thinking about—we stumble on new meanings and ask new questions.

When we do, we don't only change how we interpret the data all around us. We often impact how others make sense of the world. I imagine there's a young high-jumper who watched a beaming Nicola Olyslangers scribbling in her journal after each jump and decided to do the same the next time they hit the track. By modeling a reflective and adaptive approach to her sport, Olyslangers inspires others to do the same.

As media makers, marketers, educators, managers, consultants, and colleagues, we can do the same for those who look to us for guidance or support. We can model an attention to the framework as much as an attention to the data. We can practice making sense at least as much as we practice finding the right answer. When we do, we encourage others to do the same.

Further Reading

How to Make Sense of Any Mess by Abby Covert

Thinking Systems by Donella Meadows

What Works by Tara McMullin

"The Seductions of Clarity" by C. Thi Nguyen in the *Royal Institute of Philsophy Supplement*

"Value Capture" by C. Thi Nguyen in the *Journal of Ethics and Social Philosophy*

Hope in the Dark by Rebecca Solnit