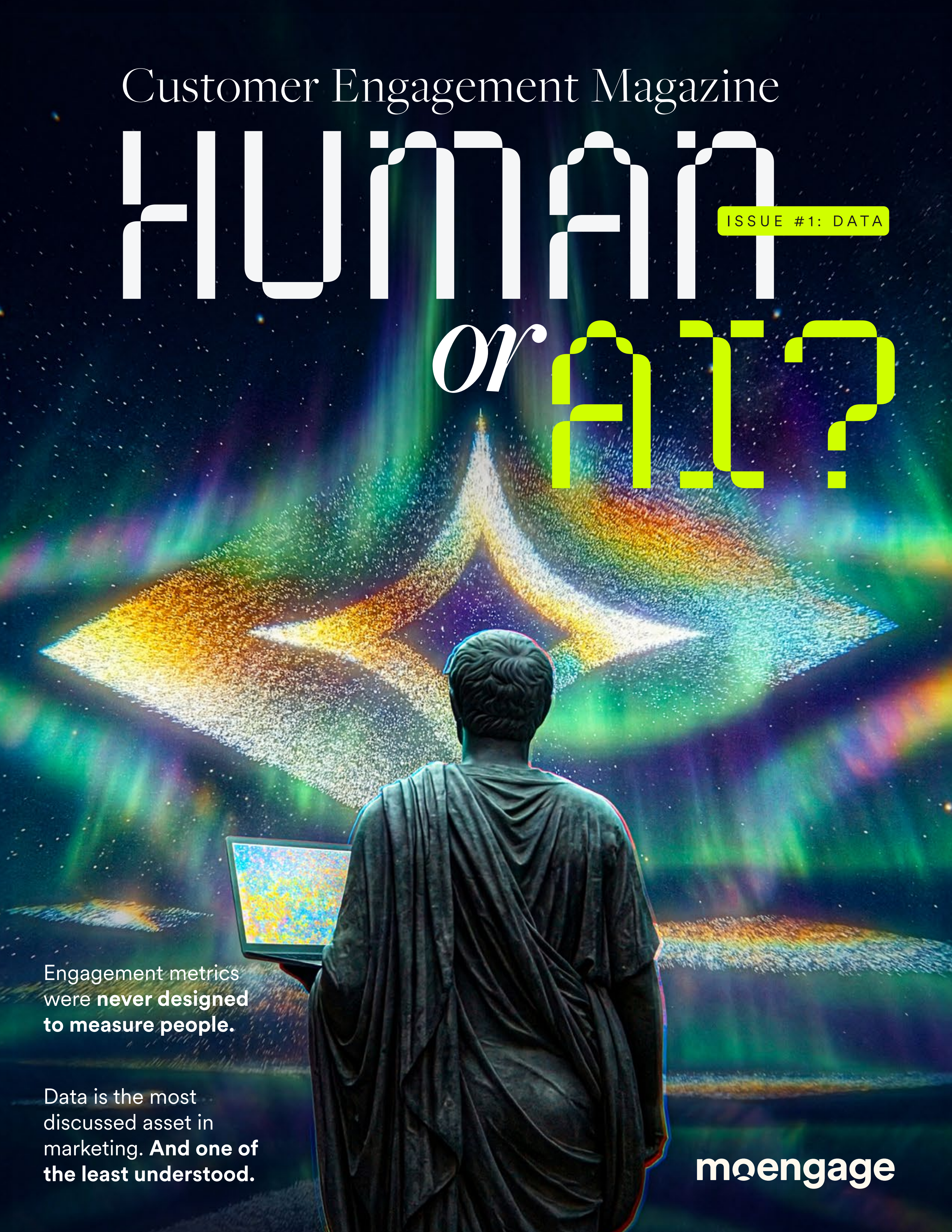
Customer Engagement Magazine

HUMAN *or* AI?

ISSUE #1: DATA



Engagement metrics were **never designed to measure people.**

Data is the most discussed asset in marketing. **And one of the least understood.**

moengage

Customer Engagement Magazine

HUMAN or AI?

ISSUE #1 | DATA

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FOREWORD

The Vision

A note from Raviteja Dodda, Founder & CEO, MoEngage

Last year, we published a Customer Engagement book. Over three thousand B2C marketing leaders downloaded it. More than seven hundred printed copies went out. It confirmed what we keep hearing: practitioners want grounded perspectives on the problems they are actually solving, in formats that are not just digital.

AI decisioning, agentic marketing, autonomous workflows. The conversation moves fast. Every week, the claims about what AI can own get bigger. But the questions from leaders about their organizations, their systems, and how they operate have not changed. How much should I hand over to AI? Where do humans stay in the loop? Where is the line between moving fast and losing control of the experience?

Nobody has a clean answer. That is why we created this magazine.

Human or AI? is not built to argue one side. We wanted practitioners to share how they are navigating that tension with real consequences attached. Three print issues this year, each covering where that tension is sharpest: data, personalization, and risk.

This is the inaugural issue. It is about data. What happens when teams give AI the authority to make decisions on a foundation that is not ready? Contributors from **Amazon Music, Calm, Fanduel,** and **Tealium**, along with martech analyst **Scott Brinker**, bring their experience to bear on that question. **Brinker** argues that customer data has become the experience, not just an input to it. **Nick Albertini** at **Tealium** describes a client that misallocated millions in ad spend after one variable was dropped during a migration. **Jeffrey Lee** at **Calm** stopped inferring user mood and started asking directly, getting a signal that behavioral data could not provide on its own. **Gary Kamikawa** at **Amazon Music** shows how AI will relentlessly optimize for whatever question you give it and why asking the wrong question is a mistake no dashboard will catch. **Bryce Macher**, formerly at **Domino's**, warns that when every brand runs the same models, only human judgment creates separation.

They work in different industries and arrived at the same place. AI does not correct a weak foundation. It scales it. When something breaks, the customer does not blame the algorithm. They blame the brand.

We built this series to give marketing leaders honest, practitioner-led perspectives on where AI helps, where it falls short, and how to set up teams so quality holds as speed increases. If the foundation is not right, the brand carries the cost.

I hope this issue is useful. Stay tuned for the next two on personalization and risk.

Editor's Note

By Shana Haynie
Head of Content and Organic Growth, MoEngage North America

There is no shortage of data.

There is, however, a shortage of clarity.

Over the past decade, marketers have been told that more data leads to better decisions. So we invested in tools, built dashboards, and expanded our ability to track nearly everything. And now, with AI layered on top, we can process and act on that data faster than ever before. But speed is not the same as understanding.

In many cases, we are making decisions more quickly without being any more certain that they are the right ones. Signals are abundant, but meaning is still hard-earned. The problem is not volume. It is knowing which signals to act on and which ones to question.

That is the tension at the center of this issue.

This first edition of the Customer Engagement Magazine: Human or AI? explores what it actually takes to move from data to decision. Not in theory, but in practice. Where systems break down, where teams get stuck, and where human judgment still plays a critical role, even as automation becomes more powerful.

Across these pages, you will see different perspectives on the same underlying questions. How do you build a system that does more than collect and visualize data? How do you create one that learns, adapts, and drives action in real time?

Some contributors argue that the future lies in fully connected systems where data, intelligence, and execution operate as one. Others point to the limits of that vision and the need for human context, interpretation, and restraint.

Both are true. Because the real shift is not from human to AI. It is from fragmented insight to integrated decision-making. And that shift does not happen just because you have more data. It happens when you know what to ignore, what to trust, and when to act.

The goal is not to become more data-driven. It is to become more decisive. And that requires more than data alone.

Meet the Contributors

Scott Brinker
has spent years studying what happens when marketing, technology, and product thinking collide. For this issue, he brings a structural argument: that customer data has quietly become part of the product itself, and that the teams who treat it otherwise are already paying for the mistake.

Nick Albertini
Global Field CTO at Tealium, has spent two decades inside the infrastructure decisions that most marketing conversations skip over entirely. He contributed the perspective most brands need but rarely want: that AI doesn't fix bad data, it just moves faster on it.

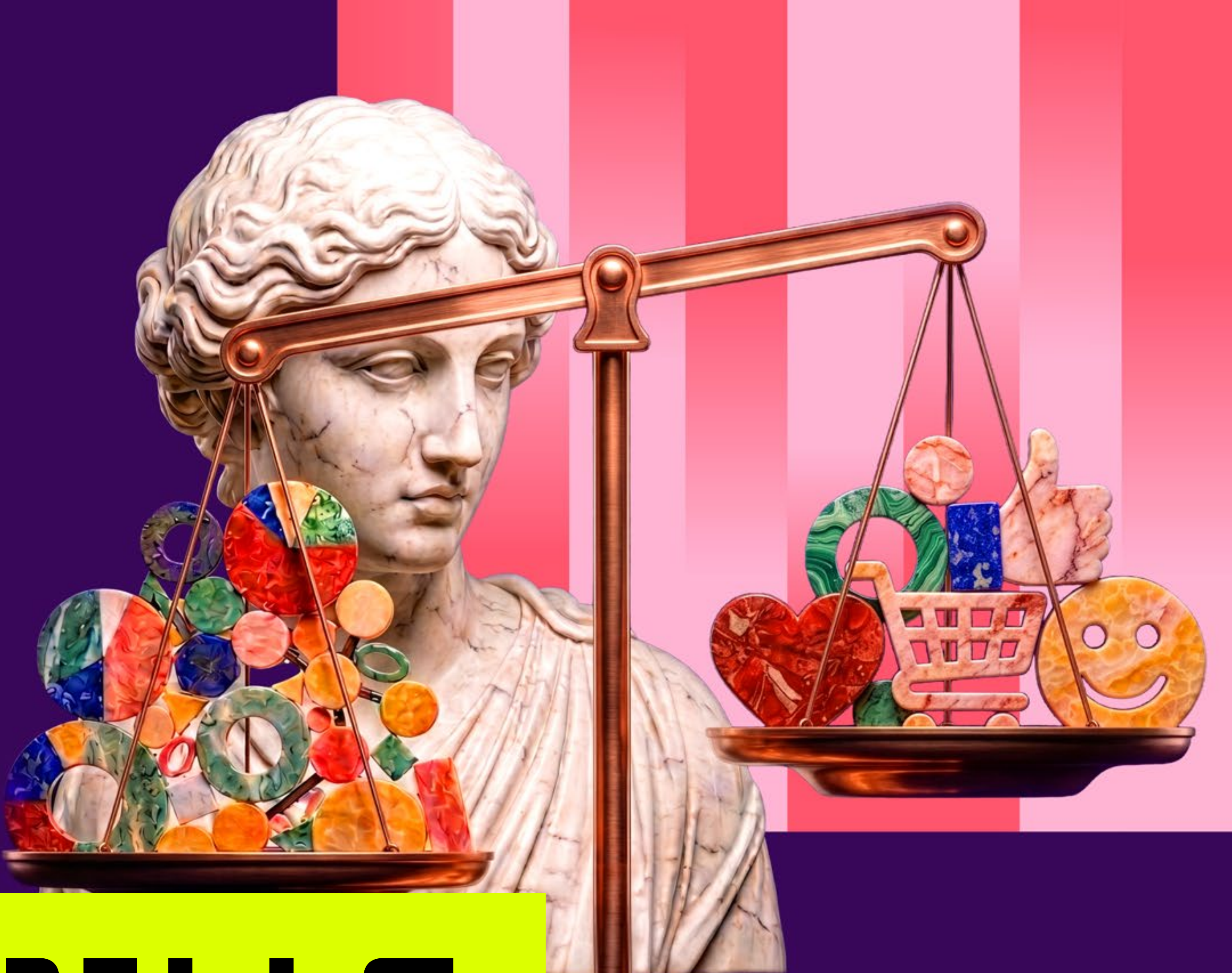
Jeffrey Lee
Lifecycle Marketing Technical Lead at Calm, works with data that carries real human stakes. Every message his team sends touches someone navigating anxiety, grief, or sleeplessness. That context shapes his view on what good marketing data actually means and why asking beats inferring, almost every time.

Bryce Macher
has built AI systems at the intersection of software engineering and data science for some of the world's most recognized consumer brands. His argument for this issue is direct: the real risk of removing humans from the loop isn't that AI gets things wrong. It's that it gets things consistently, competitively average.

Gary Kamikawa
Head of Marketing Technology at Amazon Music, sits at the intersection of engineering and marketing strategy. He thinks carefully about what AI does well, where it reliably falls short, and why the most important decisions still require someone in the room who knows the difference between a metric going up and a customer relationship actually growing.

Contributors Across Upcoming Issues Include:

Juan Mendoza (The Martech Weekly) | **Phil Gamache** (Humans of Martech) | **Stacey Hunsdon** (Pennymac)
Blair Bendel (Foxwoods Resort Casino) | **Megan Kwon** (Loblaw) | **Kevin Ertell** (Mistere Advisory)
Aboli Gangreddiwar (Credible) | **Dan Morris** (Databricks) | **Justin Keller** (Movable Ink) | **Deborah Matteliano** (AWS)
Angela Vega (Expedia) | **Katelyn Watson** (Talkspace)



THE DATA MINDSET

The most dangerous assumption in modern marketing is not that AI will replace human judgment. It is that having data is the same as understanding it. Somewhere between the signal and the decision, something gets lost. What separates the brands that notice from the ones that don't has less to do with technology than most people want to admit.

The Product Mindset for Data

When customer data becomes part of the product experience

By Shana Haynie
Featuring insights from Scott Brinker
Editor at ChiefMarTech.com

Customer data has traditionally been treated as fuel for marketing. Collect it, segment it, activate it. Feed it into campaigns, measure performance, and optimize over time.

That model worked when marketing operated downstream from the product experience. It no longer does.

Today, customer data determines what people see, when they see it, and how a brand responds to them. It shapes recommendations, powers onboarding flows, triggers notifications, and influences every interaction across channels. At that point, data is no longer supporting the experience. It is the experience.

"If your data is wrong, the experience is wrong," says Brinker. "Bad recommendations, duplicate messages, mistimed notifications, loyalty mistakes. Any of those things can really erode trust. And it's not trust in your marketing. It's trust in your company, in your brand."

Customers do not make allowances for where those failures originate.

> "Customers don't see the org chart. They don't separate a marketing problem from a data problem. They just see a company being careless, confusing, or unreliable."

Data Is Not Just Fuel. It Is the Experience.

In a traditional model, data informs marketing decisions. Campaigns are planned, executed, and measured using information about customer behavior. In a modern engagement model, data drives real-time interactions. A recommendation engine decides what product to surface. A notification system determines when to reach out. A personalization layer adjusts the experience dynamically based on behavior.

Each of these moments is powered by data. If that data is stale, incomplete, or incorrect, the experience breaks. Not gradually, but immediately.

Brinker describes customer data as a kind of digital raw material. If the raw material is flawed, the output is flawed by default. Which raises a more difficult question. If data is part of the product, who is responsible for maintaining it?

Why Ownership Is Shifting Toward Product Teams

Many organizations still manage customer data within marketing operations. Data is collected across systems, exported into warehouses, transformed into segments, and activated through messaging tools. Each step introduces distance from the source. And with distance comes degradation.

"The more translations data goes through, from database to segment to message, the more fidelity you lose," Brinker says. "The goal is to activate off the direct, live data source."

This is where product teams bring a different approach. Unlike marketing teams, product and engineering teams are built to manage systems that require consistency and reliability. They operate with clear expectations around uptime, monitoring, testing, and incident response. That discipline changes the quality of the underlying data.

"When data is owned closer to the actual systems where customer behavior is being generated, you have less lag, less handoff friction, less room for translation errors. By the time data gets translated two systems later, it's already drifted."

When data is unified and accessible in real time, messages can be triggered based on a customer's current state, not just their past activity. Marketing still plays a critical role. Strategy, brand voice, creative execution, and orchestration remain essential. But the data layer becomes more durable when it is managed as shared infrastructure, creating an accountability that neither team can own alone.

A Message Is Not Just a Message

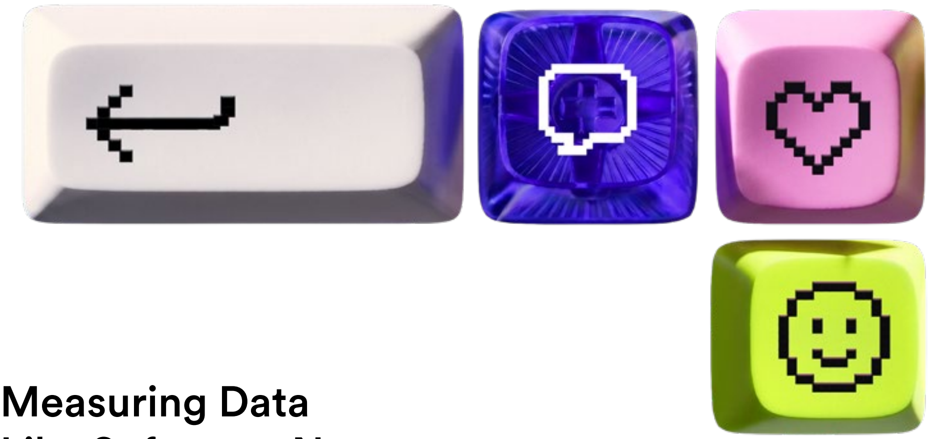
The difference between a marketing message and a product feature may seem semantic. In practice, it changes how teams operate.

"A message feels disposable. A product feature feels accountable," Brinker says. "And that difference matters in both how you think about this and the quality of what you deliver to your audience."

Marketing teams are accustomed to volume. Messages are sent, measured, and iterated. But many messages are not disposable. Fraud alerts. Shipping updates. Onboarding prompts. Renewal reminders. Account notifications. These are not promotional. They are functional. If they fail, customers do not interpret it as a missed campaign opportunity.

"It's not just that the marketing didn't resonate," Brinker says. "It's that they're not sure this is the right company to be working with."

That shift reframes how success should be evaluated. The question moves from did we send it to did it work correctly for the user in that moment. A message can generate opens and clicks while still being wrong for the customer. And one bad message can undo ten previously good ones because it signals the brand does not actually understand who it is talking to.



Measuring Data Like Software, Not Campaigns

If customer data operates like product infrastructure, it needs to be measured accordingly. Brinker describes three layers of evaluation.

The first is reliability. Is the data complete, fresh, and consistent across systems? Are events being captured and delivered correctly? These are engineering questions, but they directly determine what the customer experiences.

The second is operational quality. How quickly can teams detect when something breaks? How long does it take to resolve? How often are manual fixes required to keep systems running?

The third connects everything back to the customer. Are messages relevant? Do they lead to meaningful actions? Do they improve onboarding, retention, and long-term engagement?

The mature view of success is not about sending more messages. It is more correct experiences delivered. Measuring at the customer level is what separates teams that know their data strategy is working from teams that are simply hoping it is.

The Responsibility Behind the Experience

As customer experiences become increasingly shaped by automated systems, the line between product and marketing continues to blur. AI can help brands act faster, identify patterns, trigger interactions, and optimize at a scale that would be impossible manually. But it does not remove the responsibility to get the experience right.

Most problems organizations run into with AI stem not from the model but from the underlying data. Incomplete events, delayed signals, inconsistent identities, duplicated records.

"It doesn't matter how sophisticated the model is," Brinker says. "If your events are incomplete, delayed, or inconsistent, you're essentially giving your AI a partial picture and expecting it to make complete decisions."

The responsibility still belongs to the people designing the system. And the priority for any technical leader is not a more sophisticated model. It is a cleaner, faster signal layer.

Before you optimize the brain further, fix the nervous system.

The Data Reality Check

AI is only as smart as the signals behind it

By Shana Haynie
Featuring insights from Nick Albertini
Global Field CTO, Tealium

Artificial intelligence has become the centerpiece of modern marketing strategy. Vendors promise predictive insights, automated decisions, and personalized engagement at a scale that simply wasn't possible a few years ago.

But many brands are discovering a hard truth once the excitement fades. AI does not fix a weak foundation. It exposes one. If the data feeding the system is inconsistent, fragmented, stripped of context, or collected without verifiable consent, faster automation doesn't produce better decisions. It produces faster mistakes.

Nick Albertini, Global Field CTO at Tealium, sees this misunderstanding often as brands rush to adopt AI-driven engagement.

"AI gives us that starting point for a conversation, but it should not be the final word."

In practice, many AI failures do not begin with the model. They begin much earlier with fragmented identities, inconsistent data structures, and missing context that distort the signals the model relies on.

The Market Has Confused Prediction With Truth

Today's AI models are powerful pattern-recognition systems. They analyze historical signals and estimate the likelihood that something will happen next. But they do not deliver certainty. They deliver probabilities.

For marketers, that distinction matters more than it might appear.

A model might determine that a customer has an 85% likelihood of purchasing a product based on recent browsing behavior. That score does not mean the purchase will happen. It reflects a statistical estimate built from past patterns, one that can shift the moment new information enters the picture.

Albertini sees organizations misread these signals regularly. Marketers treat a high propensity score as a reliable indicator of future behavior, when it is closer to a hypothesis waiting to be tested.

"If you treat it as a hypothesis, then you're designing an experiment. But if you treat it as truth, you automate decisions that may not reflect reality."

That gap between prediction and interpretation is widening as AI tools move from data science teams into everyday marketing workflows. The people acting on the outputs often have little visibility into how those outputs were produced.

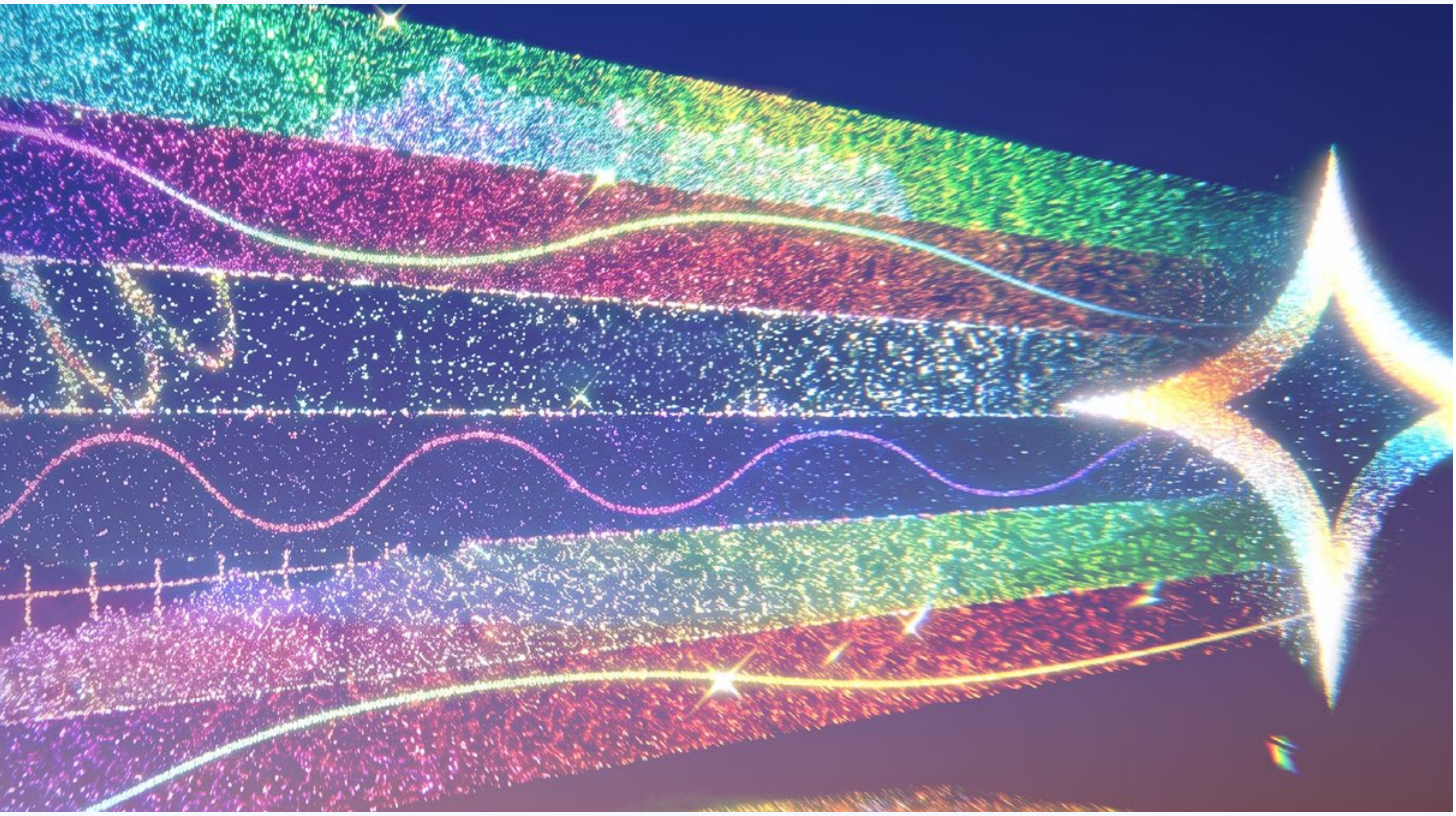
High-Performance AI Cannot Rescue Chaotic Data

Even when predictive models are technically strong, they rely heavily on the structure and reliability of the data feeding them. When that data becomes inconsistent or poorly governed, AI systems quickly lose accuracy.

This challenge is best understood through a concept familiar to data scientists: entropy. When data systems accumulate inconsistent signals, mismatched event definitions, or incomplete context, the signal-to-noise ratio deteriorates. Predictive models begin to learn from disorder rather than meaningful patterns.

"Without a universal data hub to enforce the schema at the source, your AI is essentially driving using a map of a completely different city."

Most of these issues go unnoticed until the damage is done. A web team



renames a tracking event. A mobile team adopts a different naming convention. A backend system records purchase values in a format that doesn't match the ecommerce platform.

Each change introduces friction for the model, and the costs are not abstract. Albertini recalls one enterprise client that experienced this firsthand.

During a tagging migration, a currency variable was accidentally omitted from a global advertising integration. The AI system interpreting the data assumed all transaction values were in US dollars. The company operated internationally, so purchases recorded in other currencies appeared dramatically inflated once converted incorrectly. The model interpreted the surge in transaction value as extraordinary performance and aggressively shifted advertising spend toward the campaign.

The system was not malfunctioning. It was acting on the information it received. The result was millions of dollars in misplaced advertising decisions driven by inaccurate data signals.

The principle is well understood in data science. What is less understood is how to prevent it at scale. And data quality is only part of the problem. The other part is harder to fix with better tooling alone.

When First-Party Data Becomes A Liability

First-party data is widely viewed as one of the most valuable strategic assets in modern marketing. But value and risk travel together. A brand's ability to use that data depends entirely on its ability to prove how it was collected and what it is permitted to do with it.

The exposure is direct: when collection outpaces a brand's ability to enforce privacy, that data stops being an asset and becomes a liability.

"The moment that your collection exceeds your ability to actually enforce privacy, that data becomes a liability."

Privacy regulations such as GDPR and CCPA have made consent management and data lineage baseline requirements, not competitive differentiators. But machine learning introduces a layer of complexity that most compliance frameworks were not designed to address.

When a model trains on customer data, that data becomes embedded in the model's behavior in ways that are difficult to isolate or reverse. If a regulator later determines that data was improperly sourced or collected without adequate consent, deleting the record is not enough. The organization may need to retrain the model from scratch or discard it entirely.

That is not a hypothetical. As regulators in Europe and elsewhere begin scrutinizing how AI systems are built and what they learned from, the provenance of training data is becoming a material business risk.

More data is not inherently an advantage. Ungoverned data is a liability that compounds quietly until it isn't quiet anymore. And much of it starts with a problem most brands have not fully solved.

The Boring Fix That Matters Most

That problem is identity resolution.

Customers interact with brands across many channels. A single person may appear in one system as a mobile device ID, in another as a browser cookie, and in a third as a CRM contact record. Without a way to connect those signals, the system does not see one customer moving through a journey. It sees several unrelated strangers.

The downstream effects are significant. Personalization breaks down. Consent signals become impossible to enforce consistently. And AI models trained on fragmented profiles learn the wrong patterns from the start.

"It's dreadfully boring," Albertini says. "But most AI failures are actually identity failures."

Resolving those identities changes what the system is actually working with. Albertini describes the shift simply.

"It's finally talking to a whole human being instead of a fragmented cookie."

Identity resolution will not generate headlines. But it is frequently the single change that makes everything else work better. Even so, a clean identity layer does not guarantee good decisions. It just means the system is confidently wrong about the right person.

When AI Sounds Confident But Gets The Customer Wrong

The most revealing AI failures do not show up in dashboards. They appear in moments when the output looks logical on paper but feels obviously wrong to the customer receiving the message.

Albertini calls these moments "confident nonsense," and they are more common than most marketing teams want to admit.

Consider an AI system that observes customers who receive a 20% discount tend to purchase more frequently. The model concludes that distributing discounts broadly will increase revenue. Technically, it is following the data. But many of those customers would have purchased at full price. Over time, the discounting erodes margins and trains customers to wait for promotions rather than buy on impulse. The model is optimized for the signal it was given and missed the consequence it was never asked to consider.

Context failures are just as revealing. A customer researching retirement housing might receive a back-to-school campaign if the model has no visibility into the life stage. The campaign may perform well in aggregate. But the individual experience still feels like the brand isn't paying attention.

Customers rarely understand the mechanics behind the messages they receive. They only know when the brand gets the moment wrong.

The Decision AI Cannot Make

Fixing that is not a technical problem. It is a judgment problem.

Despite the rapid evolution of machine learning, one category of decision-making will remain firmly human: contextual judgment. AI can answer what and how with remarkable precision, but the question of "should" lies entirely outside its reach.

> "AI is really excellent at answering what and how, but it's fundamentally incapable of understanding 'should.'"

That distinction is what Albertini means when he says: "We provide the soul. AI provides the scale."

The future of marketing is not a choice between human intuition and machine intelligence. It is a partnership between the two. AI still relies on humans to decide what signals actually mean and how they should be used.

The brands that succeed will not be the ones deploying the most sophisticated models. They will be the ones disciplined enough to build reliable data foundations and thoughtful enough to apply human judgment before every automated decision.

Because in the end, customers do not experience algorithms.

They experience the choices brands make with them.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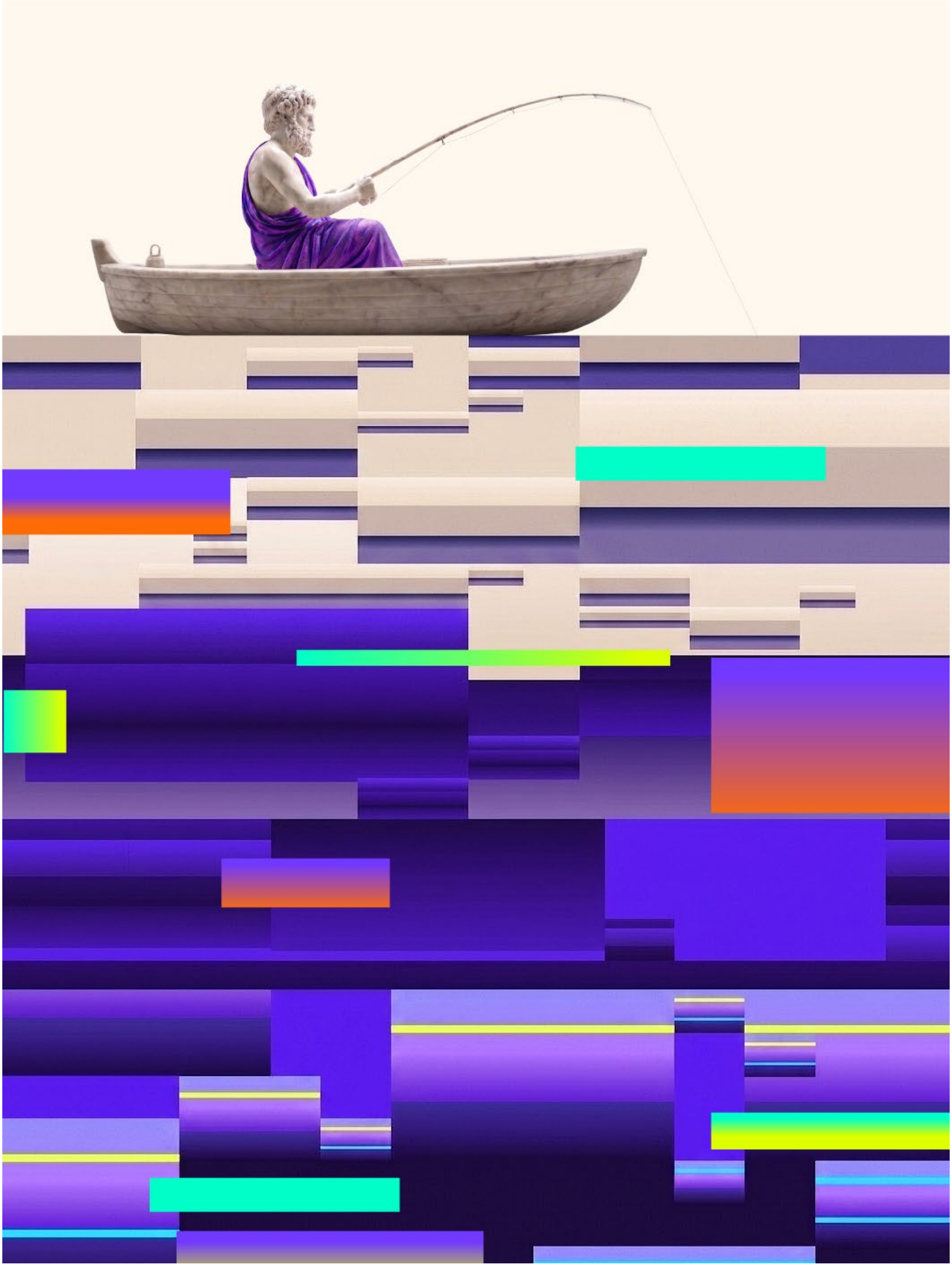


Don't Trust the Dashboard

The signals your model will never surface

By Falguni Jain
Featuring insights from Jeffrey Lee, Lifecycle Marketing Technical Lead at Calm

Most marketing data tells you what happened. A user opened an email. They tapped a notification. They completed a session. These are clean, countable signals, the kind that look good on a performance report.
But what they rarely tell you is how that person was feeling when they did it. Or why. Or whether the message that drove the click actually made their day better, or just noisier.

Engagement Metrics Were Never Designed to Measure People

Engagement metrics were designed to measure behavior. Not experience, not emotional state, not whether someone's day got better because a brand showed up well. Just behavior. And optimizing purely for behavior, without asking what it means, is how you end up with a dashboard that looks great while the relationship with your customer quietly deteriorates.

A blinking banner drives a reaction. A countdown timer creates urgency. A flood of push notifications can increase app opens. The numbers go up. The dashboard turns green. But somewhere on the other side of the screen, a real person is feeling something very different.

Calm is an unusual case study for this exact reason. The product's brand promise and its commercial success depend entirely on whether users actually feel better. That tension makes every marketing decision a values question, not just a performance question.

"If optimizing purely for engagement, data suggests we should be sending many more push notifications than we do. Campaign data also suggests we should have blinking banners and countdown timers for sales. Yes, we've tried those. And no, it's not the best experience."

It is a rare admission in an industry where the default answer to low conversion is more intensity. Lee's point is not that aggressive tactics fail in the short term. It is that they borrow trust from the future to pay for clicks today. A machine sees a five-dollar lift. A human sees a brand going against its own reason for existing.

The Most Honest Data Is the Kind You Ask For

What makes Calm's data approach distinctive is not just what they avoid. It is what they choose to do instead.

Rather than inferring user mood from behavioral signals, Calm simply asks. Mood check-ins are built into the app as a mindfulness feature, not as a data collection mechanism. Users open the app, pick an emoji, and write a short journal entry.

"Asking yourself how you feel is a mindfulness exercise. It's in the app, in the ads, in our blogs."

That design decision is worth pausing on. Because Calm built the mood check-in as a well-being tool first, users engage with it on their own terms. They are not filling out a form for a brand. They are doing something for themselves. The result is that the data Calm receives is something behavioral signals almost never produce: an honest, self-reported account of how someone actually feels in that moment.

Compare that to what an algorithm would infer. It would look at what content a user consumed and make a probabilistic guess about their emotional state based on patterns from other users. That guess might be right on average. But averages are where nuance disappears.

"An LLM is based on patterns and averages, i.e. the most likely thing. That doesn't exactly align with who you are and how you respond or react to things."

A simple illustration makes the point concrete. Someone feeling low might listen to heavy metal music to lift their mood. Someone else in the same emotional state might reach for pop. The behavioral signal looks similar, but the human behind it is completely different. A machine sees a category. A human sees a person.

Built to Not Trigger

When direct input is unavailable, Calm infers from content consumption, but only carefully. The content library is tagged by user goal and emotional need, not just format or genre. A daily meditation might carry tags like "goal=focus" and "need=sleep better". These tags were generated using AI, then reviewed by humans to verify accuracy.

That last detail matters. AI can identify patterns in a script, but it cannot assess emotional risk. It cannot judge whether surfacing a piece of content about grief to a vulnerable user at the wrong moment does more harm than good. That call requires human judgment, and Calm built it into the process by design.

"Our content team has been very cognizant of users' well-being needs. We have a tag to know if the content is sensitive; maybe it discusses grief or loss of a loved one. We'll know that we shouldn't surface something like that in the app or in an email, because we don't want to trigger any emotions." Lee says.

Most personalization systems are designed to trigger something: curiosity, urgency, or desire. Calm's system is specifically built not to. That is not a passive omission. It is an active choice that reflects a clear point of view: that the brand's relationship with its users is more important than any individual conversion. Calm deliberately reserves a portion of its push and email quota for messages that ask users to do nothing at all. No call to action. No conversion goal. Just a human moment.

Some users, Lee notes, have complained when those messages stopped arriving.

Good Campaigns Start With Instinct, Not a Brief

There is a version of data-driven marketing in which the data comes first and humans execute against it.

That is not how the process works at Calm. More often, a campaign starts with an instinct: a marketer notices a pattern, spots an opportunity, or recognizes that a new data source might unlock something worth saying. The data comes in to support the idea, not to generate it.

That instinct-first approach is not incidental. It reflects something deliberate about where human judgment sits in the process. Calm's lifecycle marketing team spots the opportunity. The data team surfaces what is actually captured and stored. Legal signs off on what can be used. And the copy team shapes the message. At every stage, a person is making a call that the data alone cannot make.

A concrete example from Calm's onboarding process makes this tangible. Calm runs a long-form onboarding quiz that captures detailed information about a user's life, goals, and habits. Whenever such a quiz is launched, the first step is simply to sit with it, sift through every question, and figure out what is actually being captured and whether it will make it into the data warehouse.

A single answer buried in fifty questions might reveal something worth acting on. But identifying which answer matters, deciding whether to act on it, and figuring out what to say about it are all human decisions. The AI-generated data creates the possibility. People determine whether to use it.

"We could use AI for the copywriting and some of the QA. But the ideation, that's not quite there yet." Lee says.

He imagines a future where machine learning helps group users by response patterns, identifying which types of people are most likely to engage with which content. The efficiency gains would be real. But the judgment calls, what to say, to whom, and when, would still belong to people.

The Person Behind the Signal

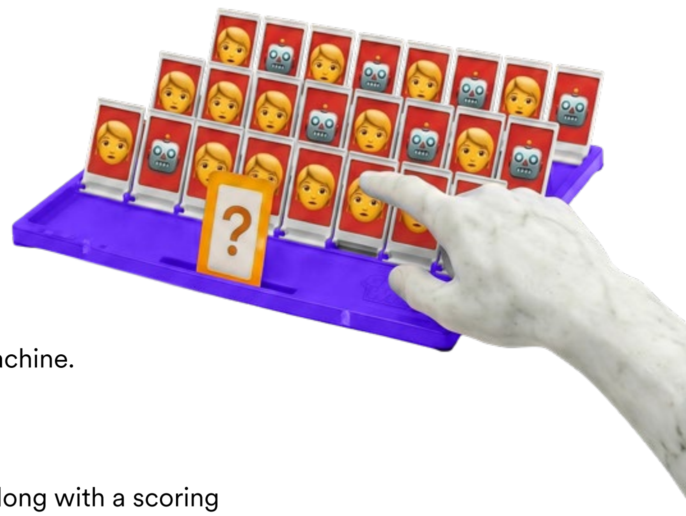
The signals Calm collects are not just behavioral data. They are traces of people trying to sleep better, manage anxiety, find focus, or feel a little less overwhelmed. That context changes what the data means and what responsible marketers are obligated to do with it.

One possibility that reflects that obligation: a message built on mood check-in history, such as "Remember, you were happy this time last month." Not a conversion play or a re-engagement nudge. Just a moment of recognition and a brand reflecting something good back to a user who shared it.

It is a small thing. But in a world of blinking banners and ten-notification days, it might be exactly what makes a person feel seen.

Because behind every signal is someone. And the brands that remember that, even when the algorithm does not, earn something rarer than a click.

Who Said It: Human or AI?



Can you spot the difference between a soul and a silicon chip?

Ten statements. Some came from a real marketer. Some came from a machine.

Your job: figure out which is which.

Circle 👨 or 🤖 next to each one. Answers are inside the back cover — along with a scoring rubric that'll tell you whether you think more like a marketer or a large language model.

1 *“The only way you get high leverage learning is by having a lot of low leverage accidents, experiments, happy accidents, intentional accidents as you test the boundaries around the world.”* 👨 🤖

2 *“The data shows a massive performance gap between marketers who personalize and those who don’t. While many see growth, those stuck in ‘broadcast’ mode are losing ground—and subscribers.”* 👨 🤖

3 *“Customer lifecycle marketing is about reaching the right people with the right message at every stage of their relationship with your brand—from first impression to lasting loyalty.”* 👨 🤖

4 *“The future is already here—it’s just not very evenly distributed.”* 👨 🤖

5 *“True understanding occurs when the silence between words becomes as meaningful as the words themselves.”* 👨 🤖

6 *“To help you build a high-performing campaign, you need to bridge the gap between ‘we are creating a newsletter’ and ‘this is a must-have resource for the modern marketer.’”* 👨 🤖

7 *"AI can handle the mundane things like generating campaign drafts, segmenting audiences, creating asset variations and assembling landing pages, which is like a massive timesaver."*

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8 *"To get this piece to a 10/10, we need to shift from 'reporting on an expert' to 'mentoring the reader.' We'll strip out the SaaS jargon, fix the mechanical errors (like those em dashes and quotes), and ensure you, the marketer, are the hero of the story."*

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9 *"I'm a big fan of marketers, particularly with the creative capabilities they bring. That being said, product teams, they're used to operating with more engineering rigor."*

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10 *"Every problem that I solved became a rule which served afterwards to solve other problems."*

THE DEEP DIVE

Automation solves the wrong problem beautifully. It makes the repeatable faster, the inconsistent more reliable, and the manual invisible. What it cannot do is make a brand worth choosing. That requires something the data has never contained: the judgment to know when the numbers are pointing somewhere a person would never go, and the instinct to go somewhere else entirely.

You Cannot Automate Your Way to Differentiation

Why the goal of automation is to protect human judgment

By Falguni Jain
Featuring insights from Bryce Macher, former VP of Decision Science at Domino's, and Jeffrey Lee, Lifecycle Marketing Technical Lead at Calm

Most marketing teams come to AI with an optimization problem in mind. They want better targeting, faster testing, and more personalization at scale. These are reasonable goals, and AI delivers on them. The numbers improve. The process gets faster. The outputs get more consistent.

But consistent is not the same as differentiated. And faster is not the same as right.

Consistency Is Not a Competitive Advantage

"As we let autonomous systems write application code and make decisions on behalf of developers, apps, websites, and email templates will all just start to look the same. And that is the problem of not having humans in the loop." Bryce Macher says.

He is describing a pattern that appears across any domain where AI is left to optimize without constraint. The system learns what works on average. It moves toward it. It keeps moving. Over time, the output stops reflecting any particular brand, voice, or point of view. It reflects the middle. Macher calls this "regression to the mean," and he sees it as the defining risk of automation done without intention.

In a market where every brand has access to the same models and the same data infrastructure, the differentiator is not who optimizes actions best. It is who introduces the right kind of decision variance at the right moment. That is a human job.

Macher's teams use AI to handle everything from generating copy to more complex customer engagement challenges. AI is well-suited to decision gates like first-pass code reviews: foundational, repetitive work that consumes developer time without requiring creative judgment. But the goal is not to replace developers. It is to free them up for work that AI cannot do.

"What we believe will happen is that advantage will come from the fact that we have highly-skilled developers who can now focus on the next cutting-edge framework, the next playbook, and the next set of capabilities."

AI models are getting better at building on what already exists. But a day-zero implementation of a new framework, a new interaction style, and a genuinely new set of capabilities still requires a person. Automate everything, and you lose the only thing that cannot be copied.

The Failures AI Will Never Let You Have

Introducing variance means tolerating failure. And most organizations are not built for that.

The conversation about human oversight is usually framed as risk management: how do we stop AI from making costly mistakes? That framing misses the more important question.

The distinction is better understood through a framework from Amy Edmondson, a Harvard Business School professor, whose work distinguishes among three types of failure. Preventable failures happen in predictable situations and should be eliminated through better processes. Complex failures occur in unpredictable environments and must be managed as they arise. The third type, what Edmondson calls intelligent failures, are the ones that actually drive progress. They happen when someone is deliberately experimenting in new territory, testing whether a boundary is really a boundary.

"I think that is the key to intelligent failures: small, controlled ways of being very intentional to generate learning by testing boundaries."

AI is very good at eliminating the first two types of failures. But in doing so, it can quietly suppress the third.

Jeffrey Lee saw intelligent failure play out firsthand at Calm. The team once gave away branded hats as part of a promotion. The promotion went viral and sold hundreds of products within a few hours. Nobody had planned for the speed of sales when a promotion goes viral. The fulfillment system kept sending out coupon codes without a safeguard that would shut it off once inventory sold out. However, Lee's team caught the problem just minutes before they would have run out of inventory.

The learning that came out of it, that free physical goods could generate the kind of enthusiasm that digital offers rarely produce, was not something that any model had surfaced. It took an accident and a human paying attention.

But humans don't just have to catch what automation misses. They also have to govern what the data is permitted to do with what it finds. This is because a system given no boundaries will follow the numbers wherever they lead, even when a human would know to stop.

The same principle applies not just to individual moments, but to entire audiences that quietly move on while the model keeps running.

AI Does Not Know When It Has Been Left Behind

AI models do not update themselves when human behavior shifts. They keep optimizing for the signal they were trained on, and they do so with increasing confidence. The risk is not that the system breaks. It is that the system keeps working, quietly and competently, for an audience that no longer exists.

"It will eventually convince itself that it is correct regardless of how much the core model measurements point to it being wrong," Macher warns.

Lee watched this happen at Calm. When he joined, mindfulness was not yet a mainstream topic. Then COVID hit. The brand appeared on CNN and SNL. A fundamentally different type of user group began to appear: people who came in through media coverage, had already tried competitors, and arrived with different expectations and varying levels of familiarity with meditation.

"The automation had been set up and probably had not changed in a few years. And now we have to look back on it and say the market of people reaching this automation is getting stale," Lee explains.

The system was not broken. It was simply no longer talking to the people it was built for. Without someone stepping back to ask that question, it would have kept running like that indefinitely.

Macher's response is to use AI to catch what AI misses. His team has been exploring different AI use cases, including the creation of synthetic audiences: generative AI agents built to embody real user segments, which can then be run against marketing campaigns to test how they respond. If the synthetic agents and the real users start behaving differently, that gap signals the model is drifting from reality.

"As that gap widens, you know that your machine is out of alignment with what actual humans are doing. You can merge what consumers are telling you already with these models, and let an independent model create a reinforcement loop to improve the system as a whole – and most likely your product managers, business stakeholders, and developers as well," he says.

This is not a replacement for human judgment. It is a way of giving humans an earlier signal that their judgment is needed. But having that warning is only useful if the organization is structured to act on it quickly.

Data Has Been the Coroner. It Now Needs to Be the Crown.

“Data teams are going to have to get comfortable making those decisions. Being the crown, and not the coroner,” Macher says.

He frames the organizational challenge with a question he thinks every data team will eventually face: Are you the coroner or the crown?

The coroner examines what has already happened, packages up findings, and hands them to the business to act on. It is rigorous, careful, and always slightly behind. The crime has occurred, and all that remains is diagnosing the aftermath. The crown, however, makes decisions in real time about what to do. It takes pride in being at the cause of a specific business context, not simply measuring the effect. The crown does not wait for full certainty. It reads the situation, weighs the risk, and moves in order to more quickly discover certainty – whether that’s success or failure.

What makes this shift possible now is speed. AI has dramatically accelerated the ability to course-correct, which means teams no longer need the same level of statistical certainty before acting. The cost of being wrong has come down, while the cost of being slow has gone up. But it requires a cultural shift.

That shift is already visible in how organizations are restructuring. Chief Data Officer roles that once reported directly to the CEO are giving way to data functions embedded inside individual business units, closer to the decisions that need to be made quickly. Chief AI Officers are rising out of the data organization, where separate full-stack teams champion driving true impact with AI. AI handles the analysis. But someone still has to wear the crown. And that person needs more than data. They need instinct.

Instinct Is Not a Bug. It Is the System.

Instinct is the difference between seeing a spike in engagement and understanding what caused it.

When Calm sent a push notification referencing the White Lotus season finale, it accidentally included a spoiler. It was an imperfect moment, and the team knew it. But what followed surprised them: engagement went up, social buzz spread, and users were drawn into Calm's broader ecosystem in ways lifecycle metrics couldn't capture.

The system saw the engagement. However, it had no way of knowing that what had actually happened was a brand showing up in a genuinely human way, acknowledging a cultural moment its users cared about. That kind of connection is not something a model optimizing for app metrics can plan for, recommend, or even recognize when it occurs.

"Capitalizing on a moment is an instinct thing. If you are only telling an AI to focus on app engagement or revenue, it will miss something like that. It is not going to know what is going on in the world, or have that human connection of: Hey, we watch White Lotus too," Lee says.

And that is not a gap in the model. It is the point. An AI system sees what happened. Only a person can judge what it means.

The One Advantage AI Cannot Optimize Away

That said, AI will always be exceptionally good at raising the floor. It catches mistakes, smooths inconsistencies, and keeps the baseline running well. However, when every brand has access to the same tools, the floor is table stakes.

The ceiling has always required a human. The variance, the instinct, the willingness to try something the data does not yet support: these are not inefficiencies to be automated away. They are what make one brand worth choosing over another. And they are the only things that cannot be replicated.

Remember, optimization is a race every brand can run. Differentiation is the finish line only humans can cross.

What Makes an AI System Learn

Why better data matters only when it improves the quality of decisions

By Shana Haynie
Featuring insights from Scott Brinker and Bryce Macher

Most conversations about AI in marketing eventually circle back to the same question: Is it working? Teams track metrics such as open rates, click-through rates, and conversion lift. They run tests, review dashboards, and report on performance. If the numbers move in the right direction, the answer is usually yes.

But that question has a more demanding version. Not just whether AI is working right now, but whether it is getting better. Whether each interaction is making the system more useful than the last. Whether six months from now, the decisions it makes will be meaningfully sharper than the ones it makes today.

That is a different kind of test. And most systems, even those built on sophisticated models, are not designed to pass it.

"AI can come back with some very smart-looking outputs," says Scott Brinker. "But just because they look smart doesn't mean they're dependable decisions."

The more useful question is no longer whether a company has AI somewhere in the stack. It is whether the surrounding system and the data flowing through it are structured in a way that allows intelligence to compound.

AI-Added Is Not The Same As AI-Ready

One of the easiest mistakes to make is assuming that once AI appears inside a platform, the system itself has become more advanced. In reality, many organizations are still operating in an AI-added environment rather than an AI-ready one.

In those environments, intelligence tends to show up in isolated moments. A model generates a score. A dashboard surfaces a recommendation. An optimization engine suggests the next best action. Each output may be useful, but the system around it is still fragmented. Data, decisioning, and execution are not working as a continuous loop. They are still happening in pieces.

An AI-ready system functions differently. It is not characterized solely by having a model. Instead, it is defined by its ability to observe behavior, respond to it, and learn from the results in a way that enhances future decisions. That is what turns AI from a feature into a capability. It is also what makes data more than raw material. In a learning system, data provides continuity, allowing each decision to carry the memory of those before it and to make the next one better because of it.

Bryce Macher brings the organizational side of that distinction into focus.

> “It doesn’t matter if your organization’s not AI-ready or AI-first. An AI-first system in an anti-AI organization is probably a recipe for wasted spend.”

That idea is critical because readiness is not purely technical. A company can buy modern systems, centralize data, and launch AI-powered workflows while still operating with old assumptions about trust, decision-making, and accountability. In that environment, the technology may accelerate activity without improving judgment.

Decision Quality Depends On Context

The primary benefit of a more mature system isn’t solely that it runs faster; rather, it makes smarter decisions by possessing a more complete context at the time of action.

When messaging tools and customer data are disconnected, decisions are often made with only partial information. A model might know what someone clicked, but not what occurred after the last message. A system may know a customer converted, but not whether they were already overloaded across other channels. It may know the next best content asset, but not whether the brand should be speaking at all. What looks like intelligence in isolation can turn into noise once the full relationship is taken into account.

“AI can make better decisions not just about what message to send, but whether to send one at all,” says Brinker.

That is a much higher bar than standard personalization. It points to a system capable of restraint, sequencing, and prioritization, not just content variation. The real advantage is not that the machine can produce more options. It is that it can make better calls about what should happen next.

Macher describes the requirement underneath that capability plainly: “Context, context, context. If you wanted to make consistent decisions, your data and your messaging have to be in the same place, because it needs that context of what’s happened to be consistent.”

Without that context, AI can still generate output. It can stay inside guardrails. It can preserve baseline efficiency. But it rarely creates much strategic advantage. At worst, as Macher puts it, it becomes “spamming people with AI.”

That is one of the clearest ways to think about data in an AI-driven environment. Data is not just the fuel behind the model. It is the memory that allows the system to behave coherently over time. Without that memory, every decision is shallower than it should be, and the system never learns that anything was missing.

A Learning System Should Improve Over Time

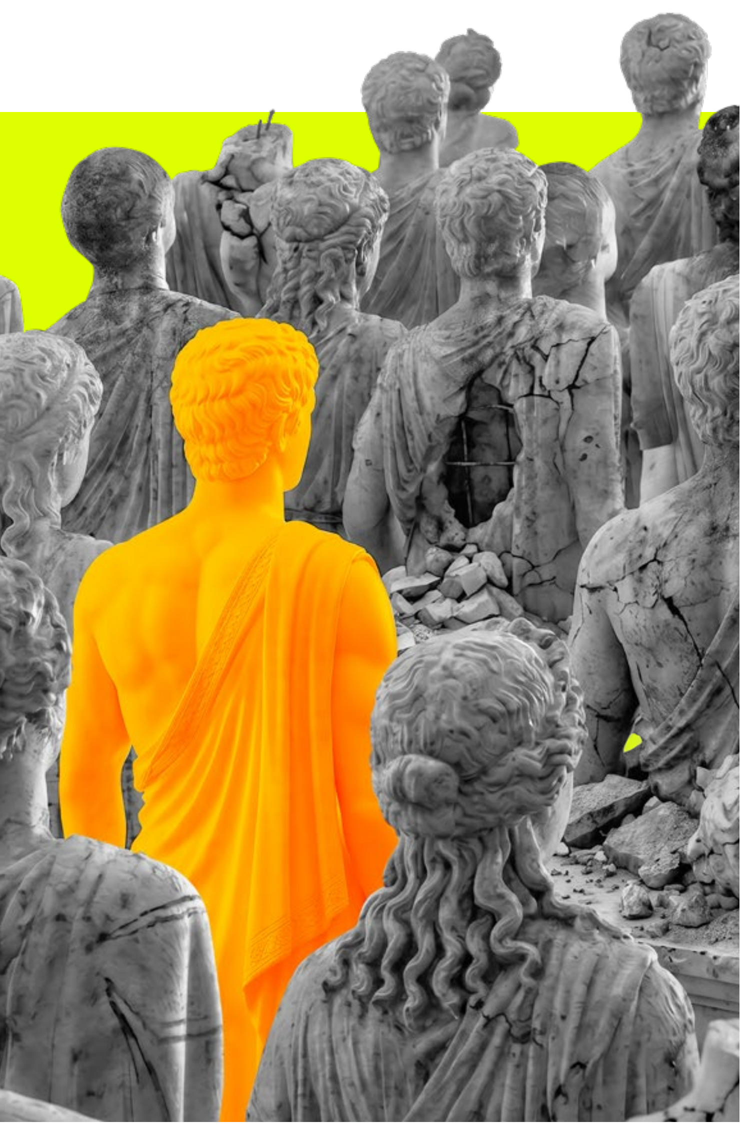
If AI maturity were only about faster execution, most brands could get there by buying enough software. The stronger test is whether the system improves as interactions accumulate.

"Part of the value is the immediate outcome improvement," says Brinker. "But part of it is also the increasing intelligence of the system itself."

That opens up a more useful way to evaluate performance. Instead of asking only whether a campaign improved this week, teams can ask whether the system is adapting as new signals arrive, whether relevance is improving over time, and whether more manual segmentation, rule-writing, and tinkering are being replaced by actual learning.

Those are harder questions than open rate, click-through rate, or short-term conversion lift. But they get much closer to what an AI-enabled system is supposed to do. A true learning system should not merely automate more tasks. It should reduce the amount of brittle manual logic required to make good decisions in the first place. That is the difference between a system that gets busier over time and one that gets smarter.

Measuring for that distinction requires resisting the pull of the metrics that are easiest to report. Speed and volume are legible. Learning is not, at least not immediately. But it is the only thing that creates a durable advantage.



Real-Time Should Not Mean Reactive

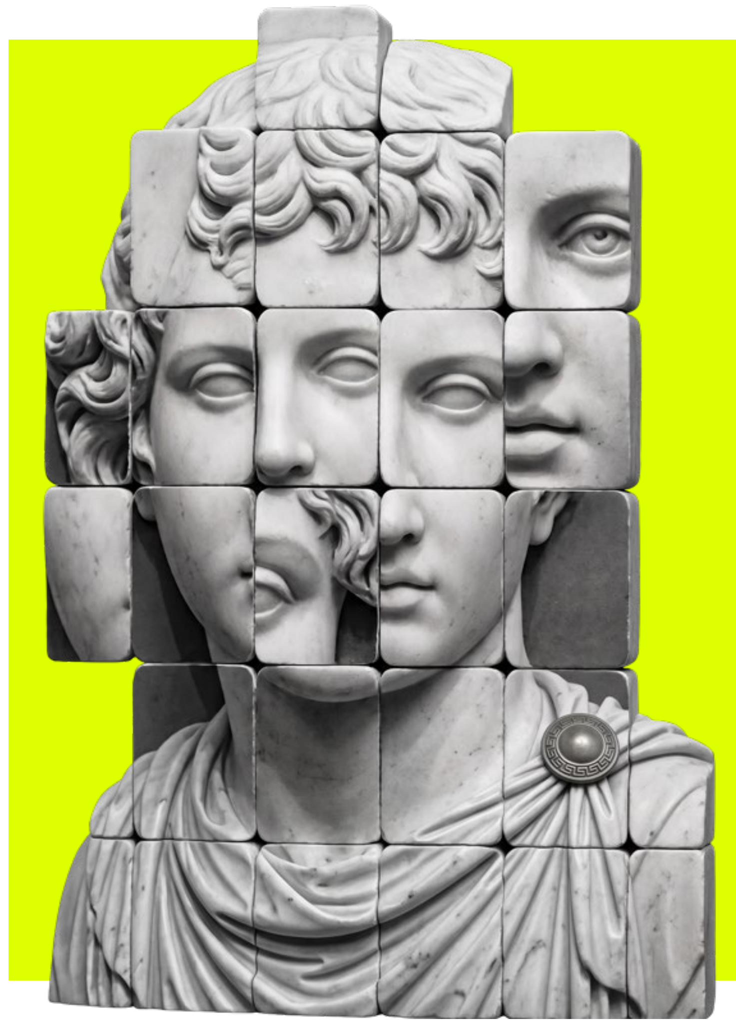
There is a trap hidden inside the promise of real-time engagement: the assumption that faster reaction automatically equals better performance. Many so-called real-time systems are really just highly responsive systems. They watch for behavioral changes, detect movement, and react quickly. That can be useful. But it can also create a false sense of maturity.

A brand that reacts instantly to every signal may still be behaving mechanically, without any deeper understanding of what matters. Shortening lag is not the same as improving foresight.

A stronger learning system does more than just close the gap between signal and response. It helps a team recognize patterns early enough to influence what happens next instead of simply chasing what has already started to unfold. The goal is not to react faster, but to react less.

Macher offers a sharper standard for measuring that value. The system should be judged by "how well it accelerates the alignment of consumer decisions and business objectives."

That is a much stronger definition of value than speed alone. It forces teams to ask whether the system is becoming more useful to both the business and the customer, not just more active.



A Wiser System Is A Stricter Standard

The gap between AI-added and AI-ready is ultimately a gap in what the system is being asked to do.

A system designed for speed and volume will get better at speed and volume. A system designed to learn from every interaction, to carry the memory of what worked and what did not, to improve the quality of judgment over time, will do something different. It will earn the right to be trusted with more.

Data matters enormously in that equation, but not because more data guarantees better engagement. It does not. What matters is whether the data flowing through the system creates continuity, context, and feedback that allows the system to understand whether its decisions are helping or hurting over time.

That is the standard worth holding. Not whether the system is active, but whether it is becoming wiser. Not whether it produces more output, but whether each decision it makes is better than the last.

A learning system should get wiser, not just busier.

It started with **one system.**

Then you added a CDP

Then a messaging tool

Then another channel tool

Then analytics

Then something to stitch it together

Then something to fix the stitching

There's a better way to run this

Make the switch. Let's talk.
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Spotlight Feature: Gary Kamikawa

The Human Behind the Data

AI is only as smart as the questions you ask it
Featuring Gary Kamikawa, Head of Marketing Technology at Amazon Music, Edited by Shana Haynie

amazon music

▶ When you bridge engineering and marketing, where do you see AI failing to understand data in ways a human marketer naturally would?

AI is very good at pattern recognition, but it struggles with context and intent. A human marketer understands cultural moments, emotional resonance, and brand perception in ways a model simply cannot. AI might see an engagement spike and assume success. But a marketer can tell whether that engagement is actually strengthening the relationship with the customer or just reflecting noise. Those are very different things, and the data alone won't tell you which one it is.

▶ What is a specific data point that AI would prioritize but a human would know to ignore?

Click-through rate is the classic example. AI may optimize aggressively for clicks, but an experienced marketer knows that curiosity-driven clicks can damage trust if the content doesn't deliver on its promise. In music, long-term listening behavior and customer satisfaction matter far more than any single click.

An example: I observed a promotion that had set the AI to maximize conversions. The system started testing how many messages it could send across email, in-app, and mobile. Because it was optimizing purely for conversion volume, it just kept pushing. At a certain point, you step back and realize you're sending more than one message a day. You may be maximizing a dashboard number, but you're also training customers to tune you out. Many people don't opt out immediately. They just stop engaging, and when you finally have something relevant to say, they've already stopped listening.

▶ You often talk about AI handling the first 60% of a task. How does that play out in practice?

AI handles the mechanical work well: generating campaign drafts, segmenting audiences, creating asset variations, assembling landing pages... Those are real time-savers. But the final 40% is where the meaningful work happens. That's the creative judgment, the brand voice, the cultural relevance, the timing. That still requires people.

A good example is what's changed with creative design. Previously, a designer would receive a brief, start from scratch, produce initial drafts, and go back and forth with the marketer before arriving at a direction. Now, a marketer using AI trained on past assets and brand guidelines can generate initial concepts themselves and hand those to the designer along with the brief. The designer goes from 60 to 100 rather than from 0 to 100. The output is better, and the team can support deeper personalization as a result.

▶ What is one creative task you will never let a machine do alone?

Defining the core narrative of a campaign. The "why does this matter" moment. Why a particular artist, album, or cultural moment deserves attention requires human intuition and taste. AI can help execute a story, but people have to define it.

The work we did with Mariah Carey a couple of Christmases ago is a good example. She had this viral moment around a giant inflatable sleigh decoration that was selling out everywhere. AI would have looked at the data, seen she was trending, and said, "Promote her." Instead, we built a game tied to that specific cultural moment, something like Flappy Bird but with Mariah on her sleigh. It played off what was happening with her brand in real time and created an experience customers actually wanted to share. AI is not going to connect those dots. That required people to pay attention to culture, not just signals.

▶ What is the danger of a hands-off approach to automation at a company the size of Amazon Music?

At scale, small mistakes compound quickly. Automation will relentlessly pursue whatever metric it's given. If that metric isn't aligned with long-term customer value, the system can slowly erode the customer relationship without anyone noticing. You end up winning the metric and losing the customer. And the hard part is that the dashboard often looks fine while it's happening.

▶ How do you ensure the systems you build are designed for human insight rather than just technical efficiency?

It starts by asking what decisions a marketer actually needs to make. Too often, systems are built around pipeline and storage rather than decision-making. We design dashboards and AI outputs around questions like: should we launch this campaign? Is this the right audience? The goal is for the system to support judgment, not replace it. Better information, but the decision still belongs to the person.

▶ How does offloading repetitive work to AI make your team more human day to day?

It removes the mechanical tasks: building segments, drafting assets, and formatting campaigns. That clears space to think about empathy, creativity, and strategy. Instead of assembling campaigns, the team is thinking about how music fits into someone's life. That's a meaningful shift in where people spend their energy, and honestly, it's the shift that makes the work feel worth doing again.

▶ When a machine generates a recommendation, what is the one question a marketer should always ask before acting on it?

Would this feel authentic or beneficial if I received it? That question forces you to consider the customer's perspective rather than just the model's confidence score. You can still tell when something feels off. It's like someone singing slightly off-key. They're singing the song; they might be close, but when they hit a wrong note, you cringe immediately. That's what happens when AI-generated content misses the mark. It's almost right, but not quite, and customers feel it even if they can't explain why. The brands that get this right are the ones where a human is still reading the output before it goes out the door.

▶ Why is an explicit signal, like a customer answering a poll, more valuable than a predictive data point generated by AI?

Because it's intentional. A prediction is an inference built from a collection of behavioral signals. But when a customer chooses to tell you something about themselves directly, that is a much stronger foundation for personalization. Understanding that someone prefers a specific artist, or has strong feelings about a particular event, gives you something real to act on. With a predictive score, you're working with what the model thinks is probably true. With an explicit signal, you know. That distinction matters more than most teams realize, and it's one of the reasons we invest in moments that invite customers to tell us what they actually want rather than just inferring it from what they clicked.

▶ How do you use data to build trust with a customer over years rather than just driving a click today?

You optimize for relevance and restraint. The goal isn't maximizing messages. It's the right message at the right moment. When customers consistently feel like a service understands their tastes without overwhelming them, trust compounds over time.

One thing we watch closely is how programs perform across different audience segments. It's easy to look at an aggregate metric going up and feel good. But when you dig in, you often find you've just gotten your most engaged customers to engage a little more. The less engaged customers haven't moved. That tells you something isn't resonating, and it's worth understanding why rather than celebrating the top-line number. Data tells you what happened. The human connection comes from understanding why it matters.

▶ What is your advice for a leader who has plenty of data but feels like they are losing the human connection with their audience?

Spend time with the customer story behind the data. Listen to the music. Use the product. Read the comments. Watch how people actually interact with what you've built. Data tells you what happened, but human connection comes from understanding why it matters to someone's life.

We made a change to the Prime experience within Amazon Music a few years ago, and there was a disconnect between what the data was showing and what customers were actually experiencing. The problem was that almost everyone on the team was using the top-tier paid account. Nobody was living inside the Prime experience day to day. It took one leader canceling their paid subscription and just using Prime to surface a string of friction points that the data hadn't captured. Once that person started calling things out, others followed. The data can show you the path a customer takes. It takes a human to understand what that path actually feels like to walk.

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The Reveal: Human or AI?

Here's who actually said what. Give yourself a point for every correct answer.

1	*"The only way you get high leverage learning is by having a lot of low leverage accidents, experiments, happy accidents, intentional accidents as you test the boundaries around the world."*	**🧑 - Human or AI? Magazine Contributor, Bryce Macher**
2	*"The data shows a massive performance gap between marketers who personalize and those who don't. While many see growth, those stuck in 'broadcast' mode are losing ground—and subscribers."*	**🤖 - Gemini Pro**
3	*"Customer lifecycle marketing is about reaching the right people with the right message at every stage of their relationship with your brand—from first impression to lasting loyalty."*	**🤖 - Claude Sonnet 4.6**
4	*"The future is already here—it's just not very evenly distributed."*	**🧑 - Fiction Writer, William Gibson**
5	*"True understanding occurs when the silence between words becomes as meaningful as the words themselves."*	**🤖 - ChatGPT 4.5**
6	*"To help you build a high-performing campaign, you need to bridge the gap between 'we are creating a newsletter' and 'this is a must-have resource for the modern marketer.'"*	**🤖 - Gemini Pro**
7	*"AI can handle the mundane things like generating campaign drafts, segmenting audiences, creating asset variations and assembling landing pages, which is like a massive timesaver."*	**🧑 - Human or AI? Magazine Contributor, Gary Kamikawa**

8 *“To get this piece to a 10/10, we need to shift from ‘reporting on an expert’ to ‘mentoring the reader.’ We’ll strip out the SaaS jargon, fix the mechanical errors (like those em dashes and quotes), and ensure you, the marketer, are the hero of the story.”*

🤖 - Gemini Pro

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9 *“I’m a big fan of marketers, particularly with the creative capabilities they bring. That being said, product teams, they’re used to operating with more engineering rigor.”*

🧑 - Human or AI? Magazine Contributor, Scott Brinker

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10 *“Every problem that I solved became a rule which served afterwards to solve other problems.”*

🧑 - Philosopher and Scientist, René Descartes

Count up your correct answers and find out where you stand.

0 to 3: You Might Actually Be a Bot

Either you are deeply, impressively wrong, or you have spent so much time talking to AI that the lines have completely blurred. We’re a little worried, but we’re not judging. The good news: you read through this magazine, which is a very human thing to do.

4 to 6: Suspiciously On the Fence

You got some right, you got some wrong, and honestly, that tracks. The trickier calls in this quiz were not the polished marketing AI or the 18th century philosopher. They were the humans who sounded like they were riffing in an interview, and the AI that sounded like it was trying to mentor you. The gray zone is not a failure mode. It is just where things actually are right now.

7 to 9: Sharp Instincts

You can feel the difference between lived experience and a very confident simulation of it. You caught the AI that hedges without vulnerability, instructs without stakes, and reaches for professionalism instead of personality. You probably also noticed the one that tried a little too hard to sound wise. That instinct is worth protecting. The models are getting better at emulating humans, but they still cannot have learned anything the hard way.

10 out of 10: You Could Spot a Hallucination in a Boardroom

Perfect score. You have an almost unsettling ability to tell the difference between something that sounds human and something that actually is. Most people cannot anymore. Hold onto that.