PRODUCT STRATEGY

Building AI Products That *Actually Work* —

What Most Teams Get Wrong

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There has never been a better time to build AI products. The underlying models are more capable than ever, development cycles have compressed dramatically, and the barrier to getting something functional into users' hands has dropped to a fraction of what it was even three years ago. For product teams, this is genuinely exciting.

It is also, paradoxically, the source of a new and underappreciated risk.

When building something was hard, the difficulty itself imposed a kind of discipline. Teams had to think carefully before committing resources. They had to be selective. The friction of development forced prioritisation. Today, that friction has largely gone, and with it, a natural check on the instinct to build first and think second.

The result is a product landscape increasingly populated by AI features that nobody asked for, AI workflows that create more complexity than they resolve, and AI products that demonstrate impressive capability while failing to deliver genuine value. The speed of building has outpaced the rigor of thinking. And the teams that succeed over the long term will be those that restore that rigor, deliberately and systematically.

01 The Problem With Starting With the Model

The most common mistake in AI product development is also the most seductive: starting with the technology rather than the problem.

It is easy to understand why this happens. A new model is released. A capability is demonstrated that feels genuinely novel — it can summarise, generate, reason, retrieve, or synthesise in ways that were not possible before. The instinct of a product team is to ask: what can we build with this? What existing workflow could this improve? What product could this power?

These are not unreasonable questions. But they are the wrong starting point. They orient the entire development effort around what the technology can do, rather than what users need. And the gap between those two things — what AI can do and what people genuinely want done — is where most AI products quietly fail.

WRONG STARTING POINT	RIGHT STARTING POINT
"What can we build with this?" — orients the entire effort around what the technology can do	A specific, well-understood problem for a clearly defined group — for which AI is the most compelling solution

The better starting point is deceptively simple: a specific, well-understood problem experienced by a clearly defined group of people, for which AI represents not the only conceivable solution, but the most compelling one. This reorientation changes everything — the design decisions made, the metrics chosen, the features built, and the trade-offs accepted.

02 Capability Is Not Value

A product that is technically impressive and a product that is genuinely useful are not the same thing. The AI product landscape is full of the former. The latter is considerably rarer.

Capability describes what a system can do. Value describes what changes for a user because of it — what becomes faster, easier, less costly, less uncertain, or more possible. The distance between those two things is often larger than development teams anticipate, and it is crossed not through engineering but through design: the careful, iterative work of understanding how real people in real contexts encounter real problems, and shaping a product that meets them there.

· Capability	· Value	· The bridge
What a system can do under ideal conditions on a benchmark	What becomes faster, easier, less costly, or more possible for a real user	Careful, iterative design in real-world conditions — not engineering alone

This distinction matters because it changes where teams should invest their attention. Optimising model performance is valuable only insofar as it translates into something the user experiences as better. A system that is 15% more accurate on a benchmark but no more useful in practice has not improved. A system that is technically simpler but meaningfully easier to use has.

The measure of an AI product is not what it can do in ideal conditions. It is what it reliably does for its users, day after day, in the messy, unpredictable conditions of actual use.

03 The Trust Problem

AI products face a challenge that most software products do not: users must not only find them useful, they must trust them enough to rely on them.

This is a meaningful distinction. A user can adopt a conventional software tool while remaining largely indifferent to how it works. The behaviour is predictable, the outputs are deterministic, and errors — when they occur — tend to be consistent and diagnosable. AI systems behave differently. Their outputs vary. They can be confidently wrong. They can perform brilliantly in one context and poorly in another that appears superficially similar. And users, quite reasonably, want to understand the degree to which they can depend on what a system tells them before they act on it.

Trust in AI products is not built through capability alone. It is built through:

Transparency	Calibration
Helping users understand what the system is doing and why	Ensuring the system's confidence is well-founded and uncertainty is communicated honestly rather than concealed
Reliability	**Recoverability**
Performing consistently enough that users can form accurate expectations	Making it straightforward for users to identify, question, and correct outputs that are wrong

Teams that treat trust as a design principle from the outset build very different products from those that treat it as a post-launch concern. The former earn adoption. The latter manages complaints.

04 The Iteration Imperative

AI products are not finished at launch. This is true of all software, but it is especially true of AI, for a reason that is specific to the technology.

Conventional software behaves as designed. AI systems behave as trained and prompted, and the gap between intended behavior and actual behavior in production is often significant. Real users interact with AI products in ways that development teams do not fully anticipate. Edge cases that seemed unlikely in testing turn out to be common in practice. Failure modes emerge that were invisible in controlled environments.

This means that the feedback loop between deployment and development is not optional — it is structurally necessary. Teams need to observe how their product performs in the wild, understand where and why it fails, and use that understanding to improve continuously.

> *"The product that launches is not the product that succeeds. The product that succeeds is the one that has been systematically improved in response to real-world evidence."*

This has implications for how AI product development should be resourced and structured. The instinct in many organisations is to treat launch as the conclusion of an effort. For AI products, it is more accurately the beginning of a different kind of effort — one that requires ongoing investment in monitoring, evaluation, and refinement that never fully ends.

05 What Gets Underestimated: The Human Layer

Across the AI products that underdeliver, one factor appears with striking consistency: an underestimation of the human layer.

The human layer is everything that sits between the technology and the outcome — the user behaviors, workflows, mental models, organisational contexts, and social dynamics that determine whether an AI product actually changes anything. It is where the most sophisticated models encounter the most fundamental resistance. And it is where the most important design decisions are made.

This means understanding not just what users say they want, but what they actually do — how they currently complete the tasks an AI product is designed to support, what they trust, what they resist, and what incentives shape their behavior. It means designing for adoption as deliberately as for functionality, recognising that the best AI product in the world creates no value if the people it is designed to help choose not to use it, or use it incorrectly, or use it in ways that undermine rather than amplify its potential.

It also means taking seriously the question of what happens to human judgment in systems where AI plays a significant role. The goal of a well-designed AI product should not be to displace human thinking, but to augment it — to make people more capable, more informed, and more effective than they would be without it. Products that are built around this principle tend to earn deeper adoption and generate more durable value than those designed primarily to automate.

Principles for Building AI Products That Last

The organisations and teams consistently building AI products that deliver real value share a set of commitments that distinguish their approach from those chasing speed and novelty.

- **Start with the problem, not the technology** — defining with precision what they are trying to solve, for whom, and why AI is the right tool to solve it.
- **Design for trust from day one** — treating transparency, calibration, and recoverability not as features to be added later, but as foundational to the product's credibility and adoption.
- **Treat launch as the start of the learning process** — investing in the monitoring, evaluation, and iteration infrastructure needed to improve continuously in response to real-world use.
- **Take the human layer seriously** — designing for how people actually work, think, and behave, rather than how it would be convenient for them to behave.
- **Measure what matters** — defining success not in terms of technical benchmarks or usage statistics, but in terms of the genuine outcomes their product was designed to produce.

Building for What Comes Next

The AI product landscape will continue to evolve at speed. Models will become more capable. New interaction paradigms will emerge. The frontier of what is technically possible will keep moving.

But the principles that distinguish AI products that work from those that do not are unlikely to change. Problems still need to be understood before they can be solved. Users still need to trust what they rely on. Organisations still need to support the human change that meaningful technology adoption requires. And value is still defined not by what a product can do in a demonstration, but by what it reliably delivers in practice.

The teams that build on these foundations — rather than chasing each new capability as it emerges — will be those that create something worth building: AI products that earn a genuine place in how people work, decide, and operate.

> *"That is a harder thing to build than a demo. It is also the only thing worth building at all."*