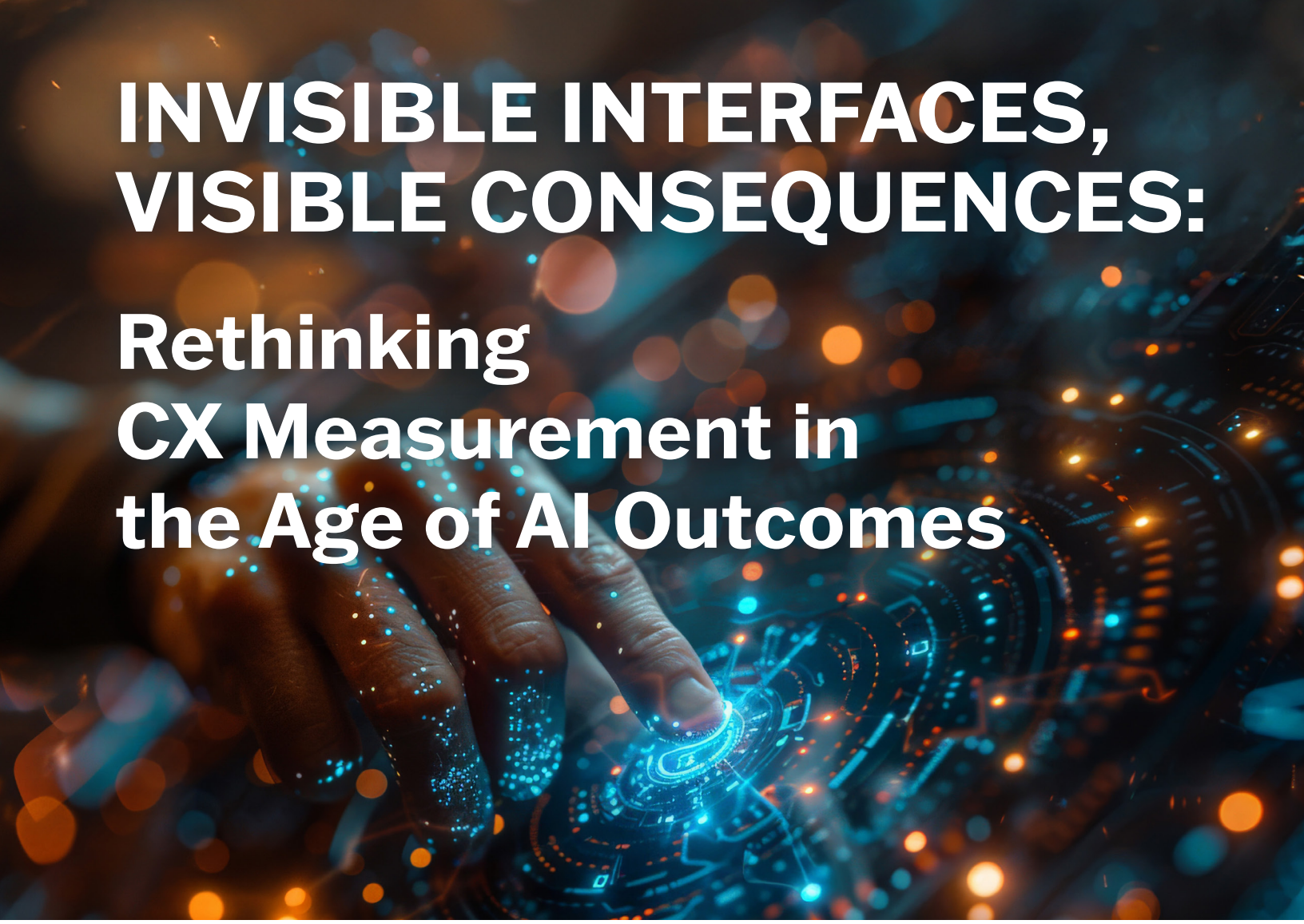

# INVISIBLE INTERFACES, VISIBLE CONSEQUENCES:

# Rethinking CX Measurement in the Age of AI Outcomes

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**The interface is disappearing — and with it, the way we measure experience.** As AI takes over more of the customer relationship, the familiar journey of steps, screens, and interactions is vanishing. What once unfolded through a visible process now happens in a single, opaque instant. The customer no longer navigates; they receive a verdict — approved, denied, priced, or personalized — with no visible path leading there.

This collapse of the customer journey has made traditional CX metrics obsolete. Measures like NPS, CES, and CSAT were built for observable experiences, not invisible judgments. They cannot capture trust, fairness, or legitimacy when the process itself has disappeared.

This paper introduces the **TAR Framework** — **Trust, Alignment, and Recourse** — a new model for measuring and governing experience in an era where every decision is the interface, and every verdict defines the brand.

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# 1 The Clockwork Decision

In 1769, a Hungarian nobleman unveiled The Turk, an automaton that appeared to play flawless chess. Crowds marveled at the mechanical genius, convinced that the machine's moves emerged from pure mechanism. In truth, a human chess master sat hidden inside, guiding every move. Tom Standage's history of the machine describes how The Turk toured Europe and America for decades, confounding audiences who could only judge the contraption by the visible result: win or loss.

The process was invisible; the decision was all that could be evaluated. Those who lost to the machine had no way of knowing whether they had been beaten fairly, only whether the moves seemed sensible and the loss legitimate. Today, AI has replaced The Turk's hidden master with code — but the customer's position is much the same. The process is invisible. The decision arrives, unadorned, and the only points of contact are trust, clarity, and the emotional residue left behind.

# 2 The Disappearing Interface

The history of the user experience is, in large part, the history of the interface. For over seventy years, our primary challenge was designing the bridge between human intent and machine computation. In his seminal 1945 essay As We May Think, Vannevar Bush envisioned the "memex," a device that would allow a user to store and retrieve vast amounts of information through associative trails — a conceptual forerunner to hypertext. His vision was not just about processing power, but about the interaction: how a person could navigate complex data intuitively.

This launched a multi-decade quest in Human-Machine Interaction (HMI) to perfect that bridge. Early command-line interfaces demanded users learn a machine's language. The revolutionary work at Xerox PARC in the 1970s inverted this, creating the graphical user interface (GUI) where the machine learned to speak ours, using visual metaphors like desktops, windows, and folders. The interface became the locus of design, the tangible plane where function was made accessible.

As digital services moved from the workplace to the home, brands came to live and die on these interfaces. The interface wasn't just a means to an end; it was the brand experience. Consider the classic America Online (AOL) client of the 1990s. The friendly, modular layout, the distinct category folders, and the iconic "You've Got Mail!" audio cue were inseparable from the AOL brand itself. For millions, that interface was the internet — a walled garden where the brand's promise of simplicity and community was fulfilled with every click. Designers iterated endlessly on these flows, buttons, and page load times. We measured satisfaction with the journey.

But in AI-driven service environments, this painstakingly constructed interface often dissolves. The customer no longer navigates a process; they receive a verdict.

In banking, a user applying for a credit card like the Apple Card provides their personal information through a simple form and, within seconds, receives a decision. The complex, AI-driven underwriting process — which weighs hundreds of variables from credit history to spending patterns in a model — is entirely invisible. The user doesn't experience a journey; they are handed a verdict: approved, with a specific credit limit and interest rate, or denied.

In healthcare, a patient's medical scan is fed into an AI diagnostic system. Google's DeepMind AI, for instance, can analyze retinal scans to detect diabetic retinopathy with accuracy matching or exceeding that of human ophthalmologists. The system's internal process of analyzing millions of pixels for microaneurysms and other markers is a black box. The clinician and patient receive a verdict: a probability score or a classification of disease severity, which then informs the human medical decision.

In retail, a customer visiting Amazon sees a specific price for a product. This price is not static; it's a verdict from a dynamic pricing algorithm that has instantly weighed the user's purchase history, current demand, competitors' prices, and even the time of day. Similarly, the "products recommended for you" list is not a neutral catalog but a verdict from a sophisticated engine that has already decided what you are most likely to buy. The customer does not see the calculation; they only see the final, authoritative result.

These contexts expose a blind spot in the traditional customer experience (CX) toolkit. Net Promoter Score (NPS), Customer Effort Score (CES), and Customer Satisfaction (CSAT) were all designed to evaluate an observable interaction with an interface, or a set of interfaces. They cannot explain why two customers receiving identical outcomes might diverge sharply in trust, loyalty, and advocacy when the journey itself has become invisible.

## 3 Why Traditional CX Metrics Fail

Procedural justice research, a field of social psychology, has long shown that people's perception of the fairness of a process is often more critical to their acceptance of a decision than the outcome itself. Think of a courtroom: a defendant who believes they had a fair trial—with a competent lawyer, an impartial judge, and the chance to present their case—is more likely to accept a guilty verdict than one who feels the system was rigged. The perceived legitimacy of the process validates the result.

In invisible-interface environments, however, the customer is denied a view of the "trial." The AI's process is inaccessible, so fairness can only be inferred from the final decision and whatever explanation—if any—accompanies it. This creates a critical vulnerability for brands.

## FINANCE – THE OPAQUE VERDICT:

The Consumer Financial Protection Bureau's (CFPB) 2022 guidance mandates specific, comprehensible reasons for adverse AI-driven credit decisions. This addresses a core procedural fairness issue. Previously, a denial from a human loan officer might come with a clear reason like "insufficient credit history." The applicant understood the criteria. Today, an AI model might deny the same person because their data profile correlates with past defaults in a way that is statistically valid but humanly incomprehensible.

**Example:** An applicant for a small business loan is rejected. The legally required notice states the reason is, "Your profile did not meet the profitability threshold of our proprietary model." This opaque verdict is functionally useless. The applicant can't learn from it, correct a potential error, or understand the bank's logic. This absence of a visible, understandable process invites suspicion that the "black box" is arbitrary or biased, destroying trust far more effectively than a simple "no" ever could.

## RETAIL – THE BETRAYAL OF THE ALGORITHM:

Wu et al. (2022) found that algorithmic price discrimination directly harmed loyalty by increasing customers' feelings of betrayal. The issue isn't just that prices vary, but that the process for determining them is secret and feels unfair.

**Example:** Two loyal, long-time customers browse the same airline's website for the same flight. One customer, whose browsing history suggests price sensitivity, is shown a fare of $350. The other, whose history includes booking more expensive hotels, is shown a fare of $425. If they discover this, the damage isn't the $75 difference; it's the violation of trust. The invisible process treated them unequally, turning their loyalty into a variable to be exploited. The brand's relationship is harmed not by the high price, but by the customer's belief that the pricing process was unjust.

## GIG PLATFORMS – JUDGMENT WITHOUT APPEAL:

Kellogg et al. (2020) documented how opaque algorithmic deactivation on gig platforms destroyed worker trust and undermined the system's legitimacy. For gig workers, who operate as independent entrepreneurs, the platform's process is their workplace structure.

**Example:** A food delivery driver with a 4.9-star rating over thousands of deliveries wakes up to find they can't log in. They receive an automated email: "Your account has been deactivated for fraudulent activity." No specifics are given. Was it a glitch? A false customer complaint? The driver is locked out of their livelihood by a secret judgment from an AI moderator. The absence of a visible process for review or a channel for a meaningful appeal is devastating. It removes any sense of recourse, intensifying the loss of trust and making the entire platform feel illegitimate.

# 4 The Psychological Dynamics of Outcome-Only Experiences

The behavioral mechanics of how we react to decisions are well understood. In AI-driven contexts, these dynamics are not only present but dangerously amplified due to the inherent opacity of the systems.

**Fairness Heuristics:** People use mental shortcuts, or heuristics, to judge fairness. Crucially, they will accept negative outcomes if they believe the process was fair. For example, a driver who gets a speeding ticket is more likely to accept the fine if the officer was polite and clearly explained the radar reading. The fair process legitimizes the bad news. When an AI simply triples a ride-sharing fare due to "surge pricing," the user gets the bad news without any visible process, making the outcome feel arbitrary and exploitative.

**Transparency & Legitimacy:** Explanations are the bedrock of legitimate authority. As shown in studies of policing, when an officer explains their actions ("I pulled you over for a broken taillight"), citizens are more likely to comply because the transparency makes the officer's authority feel justified. This applies directly to AI. When a platform like YouTube removes a video with a vague notice like, "This violates our community standards," it feels like an illegitimate act of censorship. A transparent reason — "This video was removed because it contains copyrighted audio from 'Song X'" — makes the platform's authority feel legitimate and gives the user a clear path to correction.

**Recourse Confidence:** The mere belief that one could challenge a decision significantly reduces dissatisfaction, even if the option is never used. Most people who buy a shirt never use the 30-day return policy. But the existence of that policy—the confidence in recourse—gives them the psychological safety to make the purchase. When an AI system denies a business loan, the presence of a clear, accessible "Appeal this Decision" button that leads to a human review provides a similar safety net. It signals that the system is not an unchallengeable dictatorship, which makes the initial negative outcome more palatable.

**Emotional Immediacy:** Our first emotional reactions are powerful predictors of future behavior, often overriding later rational thought. When a customer's credit card is unexpectedly declined at a busy checkout counter, the immediate, pre-rational feeling is a hot flash of embarrassment and anger. This gut reaction—a "System 1" response, in Daniel Kahneman's terms—is a stronger predictor of them switching banks than any subsequent, rational analysis of their account. Because AI verdicts are delivered instantly and often in high-stakes moments, they are potent triggers for these immediate, churn-driving emotions.

In AI-driven contexts, these dynamics are compounded by a severe asymmetry of information. The decision logic is inaccessible, the criteria are opaque, and the opportunity for human dialogue is often entirely absent. This creates a perfect storm where an invisible process feels inherently unfair, unexplained decisions feel illegitimate, and the lack of recourse leaves the customer with nothing but their immediate, negative emotional reaction.

# 5 The Case for New Metrics — and the TAR Framework

If AI is restructuring the customer experience from a journey into a verdict, then our methods for measuring that experience must evolve. Continuing to rely solely on traditional CX metrics like Net Promoter Score (NPS), Customer Satisfaction (CSAT), and Customer Effort Score (CES) in these new contexts is a critical error. It's like judging a chef's cooking based on the cleanliness of the menu—you're measuring the wrong thing.

These legacy metrics were designed for a world of visible processes:

- **NPS** asks if a customer would recommend your brand, but that willingness now hinges on the perceived justice of an AI's verdict, not just friendly service or a polished interface.
- **CSAT** measures satisfaction—but satisfaction with what? The seamless app that delivered a life-altering loan denial? The metric is too broad to distinguish between satisfaction with the interface and satisfaction with the outcome.
- **CES** measures effort, but in an AI-driven world, effort can be near-zero (one click to apply) while the emotional impact is sky-high. A low-effort, high-stakes negative outcome is a recipe for churn.

These metrics fail because they cannot see or measure the judgment moment — that instant the verdict is delivered, and trust is either forged or shattered. While new measures like Perceived Fairness may seem related to traditional CSAT, they are tuned specifically to the opaque, high-stakes outcome rather than the visible process. Without outcome-level metrics, companies are flying blind — missing the single most important leading indicators of trust erosion, loyalty risk, and brand damage in the modern customer experience.

At Phase 5, we developed the TAR Framework — Trust, Alignment, Recourse — as a governance and design model built for outcome-driven experiences, where the decision is the interface. TAR was designed for contexts where AI acts with institutional authority but without the natural feedback loops of human interaction. It ensures that each verdict is explainable, consistent with institutional purpose, and challengeable by the people it affects.

- **Trust** means users believe the outcome was reached fairly and transparently, and can follow the reasoning behind it. In traditional UX, trust was built through interaction and responsiveness; in outcome-only UX, it must be built through clarity and perceived legitimacy.
- **Alignment** means the AI's decision-making remains faithful to the institution's stated role, policies, and values — even as the system adapts over time. Alignment is the guardrail that prevents quiet drift into unintended or exploitative behavior.
- **Recourse** means users retain agency: the ability to question, appeal, or override an AI-driven decision. A system that cannot be challenged is not just unaccountable; it is unsafe.

**TAR** differs from existing AI governance frameworks because it is rooted in the user's lived experience of an AI verdict. Where compliance models focus on documentation, audits, or bias testing, TAR operationalizes fairness, purpose, and agency into the real-time moment of delivery. It bridges the gap between perception metrics and structural safeguards — ensuring that the decision a user sees is not only correct, but worth trusting.

# 6 Recommended Metrics for the AI Outcome Era

To navigate this new landscape, organizations must adopt a new suite of metrics designed specifically to measure the customer's perception of an AI-driven outcome. Each of these metrics maps directly to one or more TAR pillars:

**Perceived Fairness (Trust)**
Definition:The customer's belief that the outcome, regardless of whether it was favorable, was just, unbiased, and equitable.

Rationale: This is the bedrock of trust in any system of authority, human or machine. In opaque contexts, people rely heavily on their sense of procedural justice. A feeling of unfairness is a powerful catalyst for churn and negative word-of-mouth.

Measurement: A 5-point agreement scale on the statement, "The decision I received was fair." This must be paired with a mandatory open-text follow-up: "Why do you feel this way?" The quantitative score provides the what; the qualitative text provides the crucial why.

**Decision Clarity (Trust + Alignment)**
Definition: How well the customer understands why the outcome occurred, based on the explanation provided.

Rationale: Clarity is the antidote to the "black box" problem. It demystifies the machine and makes the decision-making process feel less arbitrary. High clarity can significantly mitigate the negative feeling of an unfavorable outcome.

Measurement: "Do you understand the reason(s) for the decision you received?" with the options "Yes," "No," and "I'm not sure."

**Brand Alignment (Alignment)**
Definition: The degree to which the AI-delivered outcome and its accompanying communication feel consistent with the brand's established values and tone.

Rationale: Every AI verdict is a brand interaction. If a brand has built its identity on being "friendly and accessible," a cold, robotic, or overly complex AI-driven denial creates cognitive dissonance that erodes brand equity.

Measurement: A 5-point agreement scale on the statement, "This interaction reflected what I expect from [Your Brand Name]."

**Recourse Confidence (Recourse)**
Definition:The customer's belief that they could effectively challenge, appeal, or get a human review of the decision if they needed to.

Rationale: Measures the customer's perceived agency and power in the relationship.

Measurement: A 5-point agreement scale on the statement, "I am confident I would know how to get this decision reviewed by a person if I disagreed with it."

**Outcome Emotional Response (Trust + Recourse)**
Definition: The immediate, unfiltered emotional reaction to the decision.

Rationale: Captures the raw, "System 1" gut reaction that is a powerful predictor of immediate churn.
Measurement: An emotion-tagging question with context-specific options.

## TAR METRICS AT A GLANCE

| Metric | Question / Wording | Scale / Options | When / How Deployed |
|---|---|---|---|
| **Perceived Fairness** | "The decision I received was fair." | 5-point scale + mandatory open-text ("Why do you feel this way?") | Post-outcome micro-survey (immediate, same channel as decision: app, email, SMS) |
| **Decision Clarity** | "Do you understand the reason(s) for the decision?" | Yes / No / Not sure | Post-outcome micro-survey (linked to explanation notice or denial/approval message) |
| **Brand Alignment** | "This interaction reflected what I expect from [Brand]." | 5-point scale | Post-outcome micro-survey (embedded in branded communication of decision) |
| **Recourse Confidence** | "I am confident I would know how to get this decision reviewed by a person." | 5-point scale | Post-outcome micro-survey (often coupled with an "Appeal / Review" option) |
| **Outcome Emotion** | "Right now I feel…" | Angry / Disappointed / Confused / Calm / Relieved / Hopeful / Delighted | Post-outcome micro-survey (triggered within minutes of the verdict to capture raw affect) |
| **Passive Signals** | Unsolicited mentions of fairness, algorithms, confusion, etc. in chats, calls, or social media posts. | Continuous sentiment analysis (NLP) | Continuous monitoring (always-on scanning of customer service channels + social feeds) |

# 7 Implementation Roadmap

Adopting these metrics requires a deliberate and integrated approach. They should be embedded into the operational fabric of any organization deploying AI in customer-facing roles.

- **Post-Outcome Micro-Surveys:** The key is immediacy. Deploy lightweight, often single-question surveys within minutes of a decision being delivered. This should occur in the same channel as the decision —a pop-up in the app, a link in the denial email, an SMS message. The goal is to capture the emotional reaction before it cools and is over-rationalized.

- **Passive Sentiment Tracking:** Go beyond surveys by using Natural Language Processing (NLP) to analyze unstructured feedback. Systematically scan support chat logs, call transcripts, and public social media posts for keywords related to AI decisions (e.g., “algorithm,” “automated,” “unfair,” “confusing”). This provides a continuous, unsolicited stream of data on how your automated judgments are being perceived in the wild.

- **Data Linkage to Business Outcomes:** The real power of these metrics is unleashed when they are connected to hard business data. A data analytics team should be tasked with answering critical questions: Does a 1-point drop in Perceived Fairness scores for a specific AI model correlate to a measurable increase in customer churn over the next 90 days? Does low Decision Clarity directly predict higher call volumes to the support center? This linkage is what proves the tangible ROI of fairness and transparency.

- **Governance Integration as an Early Warning System:** These metrics are not just for the CX team; they are an essential dashboard for risk, compliance, and data science. A sudden dip in Perceived Fairness among a specific demographic can be the first quantitative signal of unintentional algorithmic bias. This can trigger a model review long before the issue escalates into a regulatory fine or a public relations crisis. It transforms perception data into a proactive governance tool.

- **Cross-Sector Benchmarking:** No company operates in a vacuum. It is vital to understand how your metrics stack up. Compare your Recourse Confidence score against your direct competitors, or look to best-in-class examples from other industries (e.g., how a top fintech handles appeals vs. your own process). This provides crucial context, sets meaningful improvement targets, and helps identify emerging best practices.

# 8 Governance and Brand Resilience

These metrics are not just diagnostic tools; they are governance instruments. In regulated sectors, they can help demonstrate compliance with fairness and transparency obligations. In brand-sensitive sectors, they can safeguard identity in environments where AI systems act as autonomous brand representatives.

Crucially, TAR-based metrics form an early-warning system. They give leadership a live dashboard of trust, showing in real time whether outcomes are experienced as fair, clear, and challengeable. A sudden dip in Perceived Fairness among a specific demographic, or a fall in Recourse Confidence scores, can surface hidden algorithmic drift long before it escalates into lawsuits, fines, or public backlash. In this way, outcome perception data functions like a canary in the coal mine for institutional legitimacy.

The potential linkage to hard business outcomes makes these measures invaluable at the governance level. While the direct quantitative impact is an emerging area of study, the business logic is clear: since brand trust is a known driver of retention, it stands to reason that a decline in Perceived Fairness—a direct measure of that trust—would serve as a powerful leading indicator for future customer churn. Following the same logic, low Decision Clarity scores are a likely proxy for customer confusion, which often translates directly into higher call volumes. Gaps in Recourse Confidence, in turn, can signal a growing sense of user powerlessness that serves as an early warning for reputational and even regulatory risk.

While the precise correlations will vary by industry and context, the underlying principle is compelling: outcome-level perception metrics are leading indicators, offering executives a chance to detect and address the erosion of trust before it materializes in lost customers or public backlash. By integrating these signals into board-level dashboards alongside financial KPIs, organizations can transform “soft” perception data into a quantifiable control system for risk management.

Beyond internal monitoring, cross-sector benchmarking gives TAR metrics additional weight. Comparing fairness or clarity scores against competitors or industry leaders not only provides context but also creates reputational benchmarks. Just as firms once competed on NPS, the next decade will likely see competition on legitimacy, with TAR metrics forming the new scorecard.

The organizations that embed TAR into governance will enjoy resilience: detecting trust erosion early, understanding its drivers, and adapting processes before reputational damage becomes irreversible. Those that do not risk discovering too late that trust, once lost at the moment of decision, is almost impossible to regain.

In the end, these instruments do more than quantify user sentiment or reduce support costs. They are the levers by which institutions preserve legitimacy in an era when decisions arrive without process and outcomes speak louder than any interface. Governance through TAR metrics is not a bureaucratic add-on; it is the operating system that keeps authority explainable, accountable, and aligned with purpose. With measurement in place, organizations can manage risk and protect reputation — but without it, every verdict risks becoming indistinguishable from arbitrariness.

Comparing **fairness** or **clarity** scores against competitors or industry leaders not only provides context but also creates reputational benchmarks.

# 9 Coda

In the 18th century, The Turk fooled audiences by hiding the human inside. Today, AI hides the process inside the code. In both cases, the visible element—the outcome—determines belief, trust, and loyalty. In Enlightenment salons, the intrigue lay in wondering what kind of mind could be at work inside the box. Now, the risk lies in not knowing at all.

The decision has become the customer experience. In a world where interfaces vanish, the only way to protect trust is to measure—with unflinching precision—the moment the verdict arrives. But measurement alone is not the shield; it is the alarm.

Without Trust, decisions are never legitimate. Without Alignment, systems drift from institutional purpose into quiet betrayal. Without Recourse, mistakes calcify into injustice. TAR is not an accessory to CX — it is the operating system for legitimacy in the age of invisible interfaces.

The organizations that embed TAR will define what it means to be worth trusting: every verdict explainable, every decision anchored in purpose, every user empowered to challenge the machine. Those that do not will learn, often too late, that in an outcome-only world, trust lost at the moment of decision is almost impossible to regain.

# FURTHER READING


Ansems, T. G. C., van de Schoot, R., & van der Helm, P. (2021). The Importance of Perceived Procedural Justice Among Detained Youths: A Multilevel Meta-Analysis. Frontiers in Psychology, 12. https://doi.org/10.3389/fpsyg.2021.753697

Bush, V. (1945, July). As We May Think. The Atlantic Monthly. Retrieved from https://www.theatlantic.com/magazine/archive/1945/07/as-we-may-think/303881/

Consumer Financial Protection Bureau. (2022, May). Consumer Financial Protection Circular 2022-03: Adverse action notification requirements in connection with credit decisions based on complex algorithms. Retrieved from https://www.consumerfinance.gov/compliance/circulars/circular-2022-03-adverse-action-notification-requirements-in-connection-with-credit-decisions-based-on-complex-algorithms/

Jarrahi, M. H., & Newlands, G. (2021). Algorithmic management in a work context. Big Data & Society, 8(2). https://doi.org/10.1177/20539517211053049

Kahneman, D. (2011). Thinking, Fast and Slow. Farrar, Straus and Giroux.

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms and the Future of Work: A Research Agenda. Organization Science, 31(1), 1–25. https://doi.org/10.1287/orsc.2019.1332

Kihwa, A. (2022). The Gig Economy & Algorithmic Management: A study of Foodora riders' perceptions of algorithmic management. [Master's thesis, Stockholm University]. DiVA portal. http://su.diva-portal.org/smash/get/diva2:1695427/FULLTEXT01.pdf

Lind, E. A., & Tyler, T. R. (1988). The Social Psychology of Procedural Justice. Plenum Press.

Standage, T. (2002). The Turk: The Life and Times of the Famous Eighteenth-Century Chess-Playing Machine. Walker & Company.

Wu, Z., Li, H., & Liu, W. (2022). How Does Algorithmic Price Discrimination Affect Consumers' Perceived Price Fairness and Repurchase Intention?. Frontiers in Psychology, 13. https://doi.org/10.3389/fpsyg.2022.846298

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Arnie Guha, PhD, is Partner and Head of Experience Design at Phase 5, where he leads innovation at the intersection of customer experience, governance, and emerging technologies. His current focus is on rethinking measurement and design for an era where AI-driven outcomes replace traditional user interfaces. A researcher, strategist, and writer, Arnie has advised global financial institutions, technology leaders, and cultural organizations on building trust, alignment, and recourse into digital systems. He holds a PhD from the University of British Columbia, and an MA and BA from Cambridge University, where he was a Nehru Centenary Scholar.

## ABOUT THE COMPANY

At **Phase 5**, we help organizations navigate the evolving intersection of customers, technology, and trust.

For more than thirty years, we've guided leading brands toward deeper customer understanding — and in today's AI-driven landscape, that means uncovering not just what customers want and do, but also what they believe.

Our four practice areas — **Brand & Communications, Innovation & New Product Development, Customer Experience, and Experience Strategy & Design** — combine research, analytics, and design to translate human insight into confident, forward-looking decisions. **Drive Bold Decisions.**