DESIGN RESEARCH REPORT

Human-in-the-Loop AI UX

for TripFix Claims Management

Designing the next-generation paralegal experience where AI does the work and humans ensure quality, defensibility, and continuous improvement

Prepared: February 2026

Synthesised from research by three independent AI analyses

Executive Summary

TripFix is transitioning from a paralegal-driven claims management tool to an AI-first platform where the system processes most claims autonomously and human legal experts review, correct, and validate AI outputs. This is a fundamental shift in UX paradigm: from the user as the worker to the user as the quality controller, strategic decision-maker, and audit trail creator.

This report synthesises independent design research from three parallel analyses covering legal technology, insurance claims automation, software development review tools, data labelling platforms, content moderation systems, cybersecurity, medical imaging, fraud detection, and emerging AI UX pattern libraries. The research converges on a single core principle:

> **Verification-first design**
>
> The interface must make it cheap for a reviewer to answer: "Is this correct, and can I prove it?" Systems that tether AI outputs to primary evidence—citations, highlighted spans, transparent activity trails—reduce reviewer effort and improve defensibility. Every AI recommendation should point to the exact evidence that supports it, and visibly flag when evidence is insufficient.

The research is organised into six sections, each representing a critical design domain:

- **1. Operating Model & Constraints —** the legal, regulatory, and practical context that shapes every UX decision.
- **2. Workflow Automation & AI Handoffs —** exception-based processing, tiered autonomy, and confidence-based routing.
- **3. Dashboard & Queue Design —** the three-zone command centre and smart triage patterns.
- **4. Review & Feedback UX —** the review workbench, inline correction, and passive feedback collection.
- **5. Trust, Transparency & Explainability —** confidence visualisation, reasoning trails, and trust calibration.
- **6. Governance, Auditability & Compliance —** provenance models, audit trails, and regulatory alignment.

The report concludes with a cross-domain exemplar comparison, a consolidated pattern library, KPI framework, and an implementation roadmap.

1. Operating Model & Design Constraints

Before diving into interaction patterns, TripFix's design team must reckon with the constraints that make legal claims work fundamentally different from generic AI-assisted workflows. These constraints are not peripheral—they shape every UX decision.

1.1 The Reviewer Is Not Editing a Draft

A practical consequence for TripFix: reviewers are not merely editing AI drafts. They are performing quality assurance under time pressure, and often creating an evidentiary record that must stand up to escalation, dispute, or audit. The UI must therefore make it easy to: (1) see what the AI did, (2) verify against source evidence, (3) correct efficiently, (4) justify and annotate decisions, and (5) prove accountability through traceability.

1.2 Regulatory & Professional Constraints

- **Professional responsibility:** Legal professionals remain accountable for work product and must manage risks (confidentiality, competence, accuracy) when using generative AI. The Law Society of Ontario, the ABA, and the Canadian Bar Association all emphasise this.
- **Privacy frameworks:** Canadian PIPEDA principles and GDPR (for EU data) require limiting use, disclosure, and retention of personal data—directly impacting how AI prompts, outputs, and audit logs are stored, and how redaction and privilege controls function.
- **AI governance standards:** NIST AI RMF, ISO 42001, and the EU AI Act push toward explicit risk mapping and measurable controls. Human-in-the-loop review should be treated as a specified control with measurable effectiveness, not just a workflow preference.

1.3 Participation Models: HITL, HOTL, and Hybrid

The distinction between Human-in-the-Loop (active participation in every decision) and Human-over-the-Loop (passive monitoring with exception-based intervention) is critical for scaling. TripFix needs a hybrid: HITL for complex liability assessments and novel claim types, HOTL for routine data extraction and administrative filing. The system should clearly indicate which mode applies to each claim and why.

> **Design implication**
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> TripFix's UX must be configurable—policy rules, templates, routing thresholds, and audit settings—rather than hard-coded. The specifics of jurisdictions, claim volumes, SLAs, and evidence types will vary, and the system must accommodate this without requiring engineering changes.

2. Workflow Automation & AI Handoffs

When AI handles 80-90% of claims, the UX must shift from "here's your to-do list" to "here's what needs your expert judgment." The exception-based processing model inverts the traditional queue where everything lands on a human's desk.

2.1 Exception-Based Processing

The dominant pattern across legal tech, insurance automation, and content moderation is exception-based review. AI handles the straightforward work end-to-end; humans focus on exceptions—claims that are ambiguous, high-risk, or where AI confidence is low.

Straight-Through Processing (STP) in insurance claims automation now achieves 65%+ STP rates. The UX challenge becomes designing for the remaining 35% while maintaining audit visibility into the automated 65%. TripFix should target a tiered model: auto-resolved claims, flagged-for-review claims, and escalated-to-specialist claims.

2.2 Tiered Autonomy Model

The emerging best practice is to map autonomy to confidence and risk, not to apply a uniform review depth to every claim:

- **Tier 1 — Full Automation:** routine data extraction, deadline calculations, document formatting. Auto-completed with optional sampling QC by an operations manager.
- **Tier 2 — AI Draft + Spot Check:** standard claims where AI generates the full work product and a paralegal reviews a summary view. The reviewer confirms facts, eligibility rationale, and outbound communication.
- **Tier 3 — AI Assist + Full Review:** complex, high-value, or novel claims where AI provides evidence gathering and a recommendation, but the paralegal works through the full analysis. Requires senior lawyer sign-off.

2.3 Confidence-Based Routing

Confidence must be operationalised as routing policy, not displayed as decoration. A pragmatic approach defines thresholds at two layers:

- **Claim-level tier:** overall routing to auto-approve, needs-review, needs-senior-audit, or needs-compliance-attention.
- **Sub-task-level gates:** per extraction field, per legal rule application, per draft clause, per redaction decision. This supports both batch workflows and targeted attention for high-risk fragments inside otherwise routine claims.

> **Key insight from calibration research**
> Confidence is only useful if calibrated—a score of 0.9 should mean approximately 90% likely correct. Poorly calibrated confidence misleads reviewers and degrades decision quality. TripFix should implement reliability diagrams and recalibrate after major model updates.

2.4 Product Exemplars for Workflow Design

EvenUp Claims Intelligence Platform — The closest analog to TripFix. EvenUp evolved from single-purpose demand letters to full lifecycle claims AI. Their Smart Workflows auto-detect when treatment is complete and trigger the next stage (reducing 100+ day delays). AI Drafts generate documents across all case stages. Case Companion lets staff query case files conversationally during review. Study their lifecycle approach and proactive workflow triggers.

Harvey AI — Recently unified their interface so lawyers never switch between drafting, research, and review tools. Their Workflow Builder lets legal teams encode proprietary processes into reusable, no-code AI agents. Design philosophy: make reasoning visible through paper trails, citations, and logic chains. Study their unified workspace and design blog.

GitHub Copilot Mission Control — Centralises assignment, steering, and tracking of AI agent tasks. Code review combines LLM analysis with deterministic rules; suggestions can be pushed back to the agent for auto-fix. November 2025 updates added confidence scores and rationale on every review suggestion. Study their review UX and feedback architecture.

Labelbox Multi-Step Workflow Editor — Node-based visual editor for multi-step review pipelines with branching logic, AutoQA nodes (LLMs checking before humans see it), and conditional routing by confidence score. Study their visual workflow builder and quality metrics.

3. Dashboard & Queue Design

When the paralegal's primary role shifts to reviewing AI work, the dashboard becomes a command centre. It must answer three questions instantly: What needs my attention right now? How is the system performing? Are there patterns I should know about?

3.1 Three-Zone Dashboard

- **Action Zone:** Claims needing human judgment now. Sorted by urgency and impact. Displays AI confidence level, the specific reason the claim was flagged, and estimated review time. Supports bulk selection for batch processing.
- **Monitoring Zone:** Real-time pipeline overview. Claims being processed, completion rates, average confidence, STP rate trends, and SLA status. This is the operations manager's primary view.
- **Audit Zone:** Searchable history of all completed claims—both auto-resolved and human-reviewed—for compliance review, QC sampling, and pattern analysis.

3.2 Smart Triage & Prioritisation

The queue should not be a flat chronological list. It should be an intelligently prioritised, filterable view that helps the paralegal maximise impact per minute spent reviewing. Key patterns from claims and moderation systems:

- **Complexity indicators:** Each claim displays a clear classification (simple/medium/complex), the AI's confidence level, estimated review time, and specific flags or anomalies.
- **Turn-based attention cues:** Clear "what requires my attention next" signals prevent dashboard thrash—the pattern documented in Gerrit Code Review where explicit turn-taking reduces wasted checking.
- **Policy-based routing:** Beyond confidence, route by policy triggers: privilege indicators, novel jurisdiction, high monetary value, contradictory evidence, or compliance flags.

3.3 Agent Oversight Patterns

UX researcher B.P. Rigent documented seven patterns for human oversight of ambient AI agents. Three are directly applicable:

- **Overview Panel:** Real-time agent status (idle, running, paused, needs attention) at a glance.
- **Oversight Flow:** How humans resolve tasks requiring attention through approve/reject/modify workflows.
- **Event Stream Configuration:** Customisable triggers for what requires human involvement versus what auto-resolves.

Additional dashboard inspiration: CLARA Analytics (alert-based triage with actionable insights for insurance claims), V7 Labs (complexity-based routing for document workflows), and Hive Moderation Dashboard (confidence-threshold routing for content review).

4. Review & Feedback UX

The review experience is where quality and efficiency intersect. The UX must enable expert-level review while silently capturing feedback that improves AI performance over time.

4.1 The Review Triad Layout

A high-throughput review workbench should consistently present three regions:

- **Queue + triage context (left):** "What should I do next?" with filters, risk tiers, and attention signals.
- **Claim narrative + decisions (centre):** AI summary with citations, editable eligibility decision, compensation inputs, draft letter in diff view, and action buttons (Approve / Request Changes / Escalate / Defer).
- **Evidence + provenance (right):** Multi-format evidence viewer with highlighted spans referenced by AI, attachments list, redaction tools, provenance timeline, and version history with diffs.

The ergonomic rule: keep the default view "just enough to decide" but allow deep dives into evidence, policy, and history without leaving the page (progressive disclosure).

4.2 Structured Suggestion Blocks

Rather than free-form AI text, each suggestion should be a structured block containing: proposed value, confidence indicator, evidence links, and one-click actions (accept, edit, reject, needs-more-evidence). Reject should require a reason code (fast dropdown + optional comment) to feed analytics and model improvement.

Edits should be inline, not modal, following the "AI fills, human finalises" pattern from customer support agent-assist systems where suggestions appear near the content and the human chooses to send or modify.

4.3 Approval Grammar

Adopt a two-state approval model borrowed from code review:

- **Approve:** "I affirm this artefact meets standard."
- **Request changes:** "AI output is directionally correct but needs edits before approval."

Approvals should be scoped: reviewers may approve "fact extraction" but require a senior lawyer for "final demand letter wording." The UI should support multi-step approvals without forcing full re-review of already-approved sections.

4.4 Batch Processing with Guardrails

Batch review is how you minimise human cost per claim—if coupled with guardrails:

- **Queue segmenting:** Group by confidence bands and policy rules. Auto-moderate high-confidence items; route lower confidence for human confirmation (proven in moderation and fraud review).
- **Bulk actions:** "Approve selected," "Apply template," "Escalate selected," plus "Undo last bulk" and "Preview impact."

- **Built-in spot-checking:** “Approve 50 claims, sample 5 to verify first.” The operations manager controls the sampling rate by risk tier.

4.5 Passive Feedback Collection

The most effective feedback systems are built into the workflow, not bolted on:

- **Accept =** positive reinforcement.
- **Edit =** the diff becomes training data (the delta between AI output and human correction is the highest-value training signal).
- **Reject with comment =** explicit correction with a reason code.

The paralegal never thinks about “training the AI.” They’re doing their job, and the system captures the signal. This is how EvenUp, Labelbox, and GitHub Copilot all approach feedback.

> **Cross-industry insight: HackerOne’s “Shadowing” model**
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> In cybersecurity code review, AI agents “shadow” human experts as they work, creating long-term memories about architecture, institutional knowledge, and team policies. Over time, the AI replicates the expert’s judgment patterns—becoming a smarter teammate, not a static tool. For TripFix, this means the system should learn airline-specific patterns, jurisdictional idiosyncrasies, and firm-level preferences from reviewer corrections.

5. Trust, Transparency & Explainability

If paralegals don't trust the AI, they over-review everything (defeating efficiency). If they over-trust, quality drops. The goal is calibrated trust: appropriate confidence matched to actual AI performance.

5.1 Confidence Visualisation

Present confidence as a chip with tooltip that includes: calibration note, top factors/evidence links, and risk tier. Prefer "confidence + tier + reason" over a raw number. The three-tier traffic light model is well-validated:

- **Green (85%+):** High confidence. Output is likely correct; minimal review required.
- **Yellow (60-84%):** Medium confidence. Subtly prompts human review.
- **Red (<60%):** Low confidence. Demands human action; AI should abstain and defer.

For TripFix, show confidence at multiple levels: per-field (e.g., "passenger name: 98%" vs. "compensation amount: 72%"), per-section, and per-claim overall.

> **Radiology UX paradox**
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> In medical imaging research, 80% of radiologists preferred a complex interface with overlays and confidence scores, yet their diagnostic performance actually improved most with simple text-only output. Lesson for TripFix: test which confidence presentations improve reviewer accuracy rather than assuming more visual detail is better. The most efficient design may minimise visual noise and focus on clear, text-based directives.

5.2 Reasoning Trails & Explainability

In legal work, confidence scores alone are insufficient. Professionals need to understand why the AI reached a conclusion—the reasoning chain, evidence cited, and rules applied.

- **Harvey's Paper Trail:** Surfaces thinking steps and citations; users can backtrack through logic, verify sources, confirm citation accuracy. Design philosophy: "not a black box."
- **Stream of Thought (Shape of AI):** Bounded box showing AI logic via three expressions: human-readable plans, execution logs (tool calls/results), and compact reasoning summaries. For TripFix, this could be an expandable "AI Reasoning" panel per claim.
- **"Insufficient evidence" as a first-class state:** Explainability guidance emphasises communicating knowledge limits. The UI must clearly surface when the AI cannot make a reliable determination, not just hedge with medium confidence.

5.3 Trust Calibration Over Time

Trust is not static—it must be earned through consistent performance data. The "Trust Ladder" framework describes systems progressing from Tier 0 (experimental) through higher tiers as they demonstrate reliability within defined scopes.

The most effective technique: show confidence alongside historical accuracy. "For EU261 delay claims under 3 hours, the AI has 97% accuracy over the last 6 months" is far more trust-building than a generic percentage. TripFix should build a feedback loop dashboard showing AI performance by claim type, complexity, and time period.

6. Governance, Auditability & Compliance

For a legal claims system, governance is not an afterthought—it is a core UX requirement. Every human intervention must be logged, every AI decision must be traceable, and every output must be defensible.

6.1 Provenance Data Model

TripFix needs a data model that can answer: “What did the AI do?”, “What did the human approve?”, “What evidence supports this?”, and “What changed over time?” Using a provenance-inspired structure (W3C PROV model: entity/activity/agent), the key entities are:

- **CLAIM → EVIDENCE_ITEM:** what evidence exists for this claim.
- **CLAIM → AI_RUN → AI_OUTPUT → AI_CITATION:** what the AI produced and what it cited.
- **CLAIM → REVIEW_TASK → REVIEW_ACTION → OUTPUT_VERSION:** what the human reviewed, decided, and changed.
- **AUDIT_EVENT:** immutable log entries linking users, actions, timestamps, and artefacts.
- **POLICY_RULE → REVIEW_TASK:** what policy drove the routing decision.

This model supports version comparisons, provenance timelines, role-based accountability, and regulatory audits.

6.2 Audit Trail Requirements

Implement immutable audit events for: AI runs (inputs, model version, policies applied), AI outputs, reviewer actions (approve/reject/edit + reason codes), escalations, and outbound communications. Expose the audit trail as a scrollable timeline in the review interface (not hidden in admin panels).

6.3 Privilege, Redaction & Retention

- **Redaction tools:** Expose redaction in the review workflow (not an afterthought). E-discovery tools like Relativity provide manual and rule-based redaction with reviewer-friendly markup—directly portable patterns for claims evidence handling.
- **Retention controls:** Reviewers need visibility into retention class and sensitivity level. Audit logs must be designed with retention schedules and purpose limitation from the start. Retrofitting compliance is far more expensive than building it in.
- **Privilege handling:** Flag potentially privileged communications before they reach outbound artefacts. The system should support both automated detection and human override.

7. Cross-Domain Exemplar Comparison

The following table maps 12 production systems across the dimensions most relevant to TripFix's design. Use this to identify which products to study for specific interaction patterns.

Exemplar	Industry	Human Role	AI Task	Latency	Key Takeaway for TripFix
GitHub PR Reviews	Software	Code reviewer	Workflow + checks; AI review with suggestions	Async	Permissioned approvals, inline comments, version diffs, two-state approval grammar
Gerrit Code Review	Software	Reviewer	Workflow + versioning (patch sets)	Async	Explicit version/patch set concept; attention set reduces dashboard thrash
Relativity aiR	Legal e-discovery	Doc reviewer	GenAI review simulation; cites evidence	Async	Evidence-tethered output with document citations; defensible review trails
Everlaw AI	Legal e-discovery	Litigation team	Grounded answers with citations	Async	Direct citations for verification; human validation guidance
EvenUp	Legal PI claims	Paralegal/attorney	Full lifecycle claims AI; drafts + workflows	Async	Smart Workflows; Case Companion; lifecycle automation closest to TripFix
Harvey AI	Legal (general)	Lawyer	Unified AI workspace; no-code workflows	Mixed	Paper trail design; Workflow Builder; unified interface philosophy
Stripe Radar	Payments/fraud	Fraud analyst	Risk scoring; elevated risk → queue	Near-RT	Confidence-based queue routing; risk levels drive review priority
Hive Moderation	Content moderation	Moderator	Auto-mod rules; confidence routing	Near-RT	Confidence threshold triggers for human review; rule-based routing
HackerOne Code	Cybersecurity	Security expert	AI code review with XAI artifacts	Async	Shadowing/memory model; explainable AI artifacts; long-term learning
Zendesk Copilot	Customer support	Agent	GenAI suggested replies requiring approval	Real-time	Agent-approved actions as safety control; suggestions near content
Viz.ai Radiology	Medical imaging	Radiologist	Flag indications; prioritise worklists	Near-RT	Prioritisation lanes for time-critical items; simple UI beats complex UI in accuracy
Labelbox	Data labelling	Reviewer	Multi-step review pipelines; AutoQA	Async	Visual workflow editor; approve/reject with feedback; consensus review

How to use this table: Use code review exemplars for approvals and diffs. Use e-discovery tools for evidence-tethered AI output and redaction. Use fraud and moderation systems for confidence-based routing and batch processing. Use agent-assist systems for real-time suggestions with human approval gates. Use medical triage for prioritisation of time-critical claims.

8. KPI Framework & Measurement

Human-AI UX goals must translate into measurable KPIs that align with three outcomes: quality and defensibility, human cost per claim, and controlled autonomy.

KPI	What It Measures	UX Levers	Instrumentation
Output quality (task-level)	Correctness of AI outputs per extraction field, rule, and draft clause	Evidence-tethered suggestions; “insufficient evidence” flags; structured correction UI	Labelled review outcomes; precision/recall per task; error taxonomy
Review rework rate	% of claims requiring second pass after approval	Strong preflight checks; required fields; version diff	Log reopen events; measure time-to-final and touch count
Human cost per claim	Active reviewer time × labour rate + overhead	Batch review; keyboard microinteractions; bulk accept/undo; templates	Track active time separately from wall-clock; compute by claim type and risk tier
Confidence calibration quality	Whether model confidence reflects true correctness	Calibrated confidence display; threshold tuning UI; deferral behaviour	Reliability diagrams / ECE measures; recalibrate after major releases
AI auto-resolution rate	% of claims resolved without human intervention	Confidence routing; STP pipeline; sampling QC controls	Track by claim type, complexity, and time period
Correction rate by tier	How often humans override AI at each confidence level	Confidence indicators; historical accuracy display	Compare override rates across tiers; investigate when rates diverge from expected
Auditability coverage	% of decisions with complete provenance	Provenance timeline; immutable audit log; evidence linking	Model as provenance graph; enable regulatory audits
Time-to-trust	How long new paralegals reach steady-state review	Onboarding flows; calibration exercises; graduated complexity	Measure review patterns over first 30/60/90 days

9. Consolidated Pattern Library & Resources

These resources should be ongoing references for the TripFix design team:

The Shape of AI (shapeof.ai) — The most comprehensive AI UX pattern library. Six categories: Wayfinders, Inputs, Tuners, Governors (human oversight), Trust Builders, Identifiers. The Governors category is most relevant to TripFix.

Agentic Design Patterns (agentic-design.ai) — Patterns for Mission Control interfaces, confidence visualisation, mixed-initiative controls, and progressive disclosure. Named Gartner's top technology trend for 2025.

Google PAIR Guidebook (pair.withgoogle.com/guidebook) — Principles and patterns for human-centred AI products with practical case studies. Frames human-AI interaction as a bidirectional feedback loop.

Microsoft HAX Toolkit (microsoft.com/haxtoolkit) — Evidence-based best practices including the Guidelines for Human-AI Interaction: set expectations, support efficient correction, make system behaviour understandable.

AI UX Patterns (aiuxpatterns.com) — Shows how individual patterns compose into complete user experiences.

NIST Explainable AI Principles (NIST IR 8312) — Four principles: provide explanations, ensure they're meaningful, ensure accuracy, and communicate knowledge limits.

W3C PROV Data Model (w3.org/TR/prov-dm) — Standard conceptual grounding for "who/what/when produced this artefact." Maps directly to audit and traceability requirements.

UX for AI by Greg Nudelman (Wiley, 2025) — Framework around perception, reasoning, memory, and agency. The UX Magazine article on agentic UX is a good preview.

10. Implementation Roadmap & Next Steps

10.1 Immediate Design Priorities

- **1. Task decomposition workshop:** Enumerate every claim sub-task that AI will output (fact extraction, eligibility rationale, compensation calculation, draft communications). Map each to evidence sources and risk tiers. Define what must be evidence-tethered vs. assistive only.
- **2. Define autonomy tiers:** Map every claim type and processing step to Tier 1 (full auto), Tier 2 (AI draft + spot check), or Tier 3 (AI assist + full review). This taxonomy drives every other UX decision.
- **3. Design the review triad:** Build a prototype of the three-pane workbench (queue, claim decisions, evidence/provenance). Test with paralegals using real claim data.
- **4. Implement confidence scoring:** Start with three-tier model. Show historical accuracy alongside confidence scores. Test which presentations improve reviewer accuracy, not just preference.
- **5. Instrument from day one:** Implement the provenance model early. Retrofitting compromises defensibility and makes it harder to interpret outcomes.

10.2 Prototype Approach

Design two prototypes in parallel:

- **Prototype A:** Asynchronous queue-first workbench with batch processing. This is the recommended default for legal review because AI output is a discrete artefact with clear accountability.
- **Prototype B:** Real-time AI assist inside drafting for outbound communications where speed matters and suggestions are constrained to approved sources/templates.

Compare via time-per-claim and error outcomes. Run gold-set review studies with labelled representative claims including edge cases.

10.3 Products to Study

- **EvenUp:** Closest competitor. Smart Workflows, Case Companion, AI Playbooks, lifecycle automation.
- **Harvey AI:** Unified interface, Vault document review, Workflow Builder, design philosophy.
- **GitHub Copilot:** Mission Control, code review UX with confidence scores, feedback architecture.
- **Labelbox:** Visual workflow editor, multi-step review pipelines, quality metrics, AutoQA.
- **Relativity / Everlaw:** E-discovery review with citations, redaction tools, defensible review trails.
- **CLARA Analytics:** Alert-based triage, claims dashboards, performance monitoring for insurance.

10.4 Illustrative Timeline

Assuming a start in late February 2026 (dates illustrative, not prescriptive):

- **Weeks 1-3 (Discovery):** Baseline workflow mapping, KPI definitions, evidence taxonomy, policy trigger catalogue.
- **Weeks 4-7 (Prototype):** Low-fi review workbench prototype (queue + triad layout). Usability tests with paralegals and senior auditors.
- **Weeks 8-14 (Pilot):** Instrumentation (event model + dashboards). Limited pilot on one claim segment or risk tier.
- **Weeks 15-24 (Scale):** Confidence routing + sampling QC. Compliance hardening (retention, redaction, audit). Expand to additional claim types.

Govern the feedback loop

Define which reviewer feedback becomes training data, what approvals are required, and how changes are documented. This avoids uncontrolled drift and supports defensible change management. Model cards and datasheets-style internal documentation should accompany every model update.

This report was synthesised from three independent design research analyses. All product references are for design inspiration. Links and product details were verified as of February 2026.