Human-In-The-Loop Decision Systems: Advances and Future Directions

Funmilayo Ashore-Onisemo[1], Uchechi Mary-Linda Unamma[2], Ifeanyichukwu Jeffrey Okwesa[3],
[1] University of Georgia, Georgia,
United States; funmilayoashore1@gmail.com
[2] Peace House, Utah, USA; Ucheunamma91@gmail.com
[3] Barclays, New Jersey, USA; ifeanyieb96@gmail.com
Corresponding Author: funmilayoashore1@gmail.com
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Abstract
Human-in-the-loop (HITL) decision systems combine algorithmic inference with human judgment so that people supervise, correct, and complement automated components rather than being replaced by them. As machine learning is embedded in consequential decisions across finance, public administration, and security operations, the question is no longer whether to automate but how to allocate authority between people and machines so that the joint system outperforms either alone. This paper synthesizes advances in HITL decision systems and sets out a research agenda. We first clarify the HITL concept and situate it on the automation spectrum, drawing on classical models of levels of automation and function allocation. We then review four intersecting streams of progress: interaction paradigms and active learning that let people shape models efficiently; explanation and calibrated trust, where explainable AI and trust-calibration research aim to align reliance with actual system reliability; task allocation and adaptive autonomy grounded in mixed-initiative interaction; and domain applications in financial analytics, digital public services, and operational risk and cybersecurity. A described taxonomy organizes recurring HITL patterns by the locus and timing of human involvement. We next examine open challenges, automation bias and algorithm aversion, cognitive load and vigilance decrement, diffuse accountability, and the immaturity of evaluation methods that measure joint human-AI performance rather than model accuracy alone. Finally, we propose a forward agenda emphasizing calibrated-reliance metrics, adaptive and learnable task allocation, human-centered explanation, sociotechnical accountability, and rigorous mixed-methods evaluation. We argue that treating the human and the model as a single joint cognitive system is the central design principle for the next generation of decision systems.

Keywords: *human-in-the-loop, decision support systems, active learning, explainable AI, trust calibration, levels of automation, mixed-initiative interaction, automation bias*

1. Introduction

The deployment of machine learning in high-stakes settings has revived a much older question in human factors and information systems: how should responsibility for a decision be divided between a person and a machine? Fully automated pipelines are attractive for their speed and consistency, yet consequential decisions (approving a loan, flagging a benefits claim, triaging a security alert) carry legal, ethical, and reputational weight that organizations remain reluctant to surrender entirely to opaque models. Human-in-the-loop (HITL) decision systems occupy the middle ground, embedding human judgment at one or more points in the decision process so that people can supervise, override, and enrich algorithmic output [1], [2].

The appeal of HITL rests on a simple premise: humans and models fail in different ways. Models generalize poorly outside their training distribution, absorb historical bias, and lack contextual and normative understanding; people are inconsistent, fatigue, and struggle with high-dimensional statistical patterns. A well-designed joint system should let each party compensate for the other's weaknesses. Realizing this complementarity, however, is far harder than it appears. Decades of automation research show that inserting a human into a loop can introduce new failure modes, complacency, skill degradation, and confusion over who is responsible [3], [4]. The design of HITL systems is therefore not merely a matter of adding a human review step but of engineering the interaction so that the combined system is genuinely better than either component alone.

The premise of complementary failure deserves closer inspection, because it is often invoked as though it guaranteed benefit when in fact it only creates the possibility of one. Complementarity requires that the errors of the human and the model be at least partly independent and, crucially, that the joint system be arranged so that whichever party is right in a given case is the one whose judgment prevails. Neither condition holds automatically. If the human and the model draw on the same biased historical data, the analyst who trusts the same flawed heuristics the model learned, their errors are correlated, and pairing them adds cost without adding robustness. Worse, a poorly designed interaction can invert the intended logic, so that the human defers to the model precisely on the cases where the human would have been right and overrides it precisely where the model would have been right. The mere presence of two decision-makers does not produce the wisdom of two; it produces it only under conditions that must be deliberately engineered and empirically verified. A further reason complementarity is elusive is that the human's role in a HITL system is typically the harder cognitive job, not the easier one. When a model handles the routine and refers the residual to a person, the cases that reach the human are by construction the ambiguous, novel, and high-stakes ones, exactly those for which no clean pattern exists and for which the model's own uncertainty is highest. The human is thus asked to supply judgment under the least favorable conditions, often with little context, under time pressure, and after a long stretch of passively watching the automation succeed. Designing HITL well therefore means designing for the hard residual rather than the easy average, a distinction that much of the field's optimism overlooks and that motivates the emphasis, throughout this paper, on supporting the human at the moment of consequential judgment. This paper offers a synthesis of advances in HITL decision systems and articulates future directions. It is written for researchers and practitioners in analytics, digital government, and technology risk who must decide not only which model to build but how to fit it into a human decision process. Our contributions are fourfold. First, we clarify the HITL concept and locate it on the automation spectrum using established models of function allocation. Second, we review four streams of advance, interaction and active learning; explanation and calibrated trust; task allocation and adaptive autonomy; and domain applications, and organize recurring designs into a described taxonomy of HITL patterns. Third, we analyze open challenges that cut across domains, from automation bias and algorithm aversion to the underdeveloped state of joint-system evaluation. Fourth, we set out a research agenda. Throughout, our unifying argument is that HITL systems should be designed and assessed as joint cognitive systems, with the unit of analysis being the human and machine together rather than the model in isolation [5].

The remainder of the paper proceeds as follows. Section 2 establishes background and scope. Section 3 reviews advances and the state of the art. Section 4 discusses open challenges. Section 5 presents future opportunities and a research agenda. Section 6 concludes.

Contributions on an allied portfolio of studies spanning trade law and compliance, AI and data governance, and semiconductor and edge-computing engineering inform the framing adopted here [6]–[38]. Cognate work addressing digital-health platforms and AI governance for public-health equity provides complementary grounding [39]–[44]. A related stream of research on financial-fraud detection, audit analytics, and risk analytics reinforces these observations [45]–[59].

2. Background and Scope

2.1 The human-in-the-loop concept

"Human-in-the-loop" is used loosely across communities, and clarifying it is a precondition for cumulative progress. In machine learning, HITL most often refers to workflows in which human input shapes a model's lifecycle, labeling training data, correcting predictions, or steering the model interactively [1], [60]. In human factors and control engineering, the loop is the perception–decision–action cycle, and "in the loop" describes an operator who monitors system state and can intervene, in contrast to being "on the loop" (supervising with authority to interrupt) or "out of the loop" (removed from real-time control) [61]. These framings are complementary: the first concerns how humans improve models, the second how humans exercise operational authority over automated processes. Decision systems draw on both, because a deployed model is simultaneously an artifact that humans train and a component that humans oversee.

We adopt an inclusive definition: a HITL decision system is one in which human judgment is deliberately incorporated at one or more stages of a decision process that also relies on algorithmic inference, with mechanisms for the human to influence outcomes. The involvement may occur before deployment (curating data, shaping models), during operation (reviewing, approving, or overriding individual decisions), or after the fact (auditing, contesting, and feeding corrections back). This lifecycle view distinguishes HITL from both full automation and unaided human decision-making. The word "deliberately" carries weight in this definition, and marks a distinction that separates genuine HITL from its counterfeits. A human whose approval is required but who lacks the information, time, or authority to withhold it meaningfully is not incorporated into the loop in any substantive sense; they are a formality that confers the appearance of oversight without its substance. Similarly, a human who is nominally free to override but who is measured and rewarded solely on throughput will, under any realistic pressure, stop overriding. The distinction between designed-in and decorative human involvement is not a peripheral concern but the axis along which HITL systems succeed or fail, and it recurs in the discussion of accountability and the moral crumple zone in Section 4. It is also worth being explicit that "the human" in these systems is rarely a single, static role. Across the lifecycle the humans involved may be annotators labeling data, engineers shaping features, operators supervising in real time, managers setting escalation thresholds, auditors reviewing outcomes, and the affected individuals who contest decisions. These humans have different expertise, different incentives, and different relationships to the decision, and a design that serves one may disserve another. Treating "the human in the loop" as an undifferentiated category obscures these distinctions; a mature account must ask which human, at which stage, with what knowledge and what stake, is being asked to do what.

2.2 Decision support and decision systems

HITL systems are heirs to a long tradition of decision support systems (DSS), which since the 1970s have sought to augment rather than replace managerial judgment for semi-structured problems [62]. The DSS tradition contributes a crucial framing that contemporary machine learning sometimes neglects: the goal is to support a human decision-maker who retains authority and accountability, not to output a decision to be executed automatically. Modern predictive and prescriptive analytics extend DSS with far greater statistical power, but the design questions, what to present, when to intervene, how to fit the tool to the task and the organization, remain recognizably the same. Recasting machine-learning deployments as advanced decision support helps recover this accumulated wisdom. The DSS lineage also supplies a useful distinction that the machine-learning framing tends to blur: the difference between structured, semi-structured, and unstructured problems. Fully structured problems (those with clear objectives, known constraints, and well-defined solution procedures) can often be automated end to end, and inserting a human adds little. Fully unstructured problems resist formalization and remain the province of human judgment. It is the vast middle band of semi-structured problems, where parts of the task can be modeled while others demand contextual or normative reasoning, that HITL systems are properly designed to serve. Misjudging where a problem sits on this spectrum is a common source of failure: automating a semi-structured problem as though it were structured produces confident answers to the wrong question, while treating a structured problem as unstructured wastes human attention on work the machine could do reliably. There is, however, a discontinuity between classical DSS and contemporary machine-learning systems that the continuity thesis should not obscure. Traditional decision support presented transparent, often rule-based reasoning that a decision-maker could inspect and follow; modern models are frequently opaque, high-dimensional, and statistical, offering a recommendation without a legible chain of reasoning. This shift raises the stakes of the presentation problem enormously, because the human is now asked to calibrate reliance on a recommendation whose basis they cannot directly examine. Much of what distinguishes the contemporary HITL agenda from its DSS predecessor (the emphasis on explanation, uncertainty communication, and trust calibration) follows directly from this change in the epistemic character of the tool.

2.3 The automation spectrum

Automation is not binary but graded. Parasuraman et al. [61] propose a widely used framework distinguishing four classes of function that can be automated to differing degrees (information acquisition, information analysis, decision selection, and action implementation) each admitting a continuum from fully manual to fully autonomous. This decomposition is valuable for HITL design because it shows that “keeping a human in the loop” is not a single choice but many: one may automate information analysis heavily while leaving decision selection to the human, or automate routine decisions while routing uncertain cases to people. Sheridan and Verplank’s earlier levels-of-automation scale similarly arranges human–computer authority along a graded ladder from the computer offering no assistance to acting entirely autonomously [63].

Two enduring lessons from this literature frame the rest of the paper. First, higher automation is not uniformly better: intermediate levels that preserve human engagement can outperform both manual and fully automated extremes on overall system performance, especially under uncertainty [61]. Second, automation reshapes rather than eliminates human work, often shifting people from active control to monitoring, a role human perform poorly, producing the “ironies of automation” whereby the operator is asked to supervise precisely the situations the designer could not automate [4]. HITL design must confront these ironies directly.

The decomposition of automation into distinct functions repays careful use because it reveals that the level of automation can and often should differ across the stages of a single decision. A fraud-detection system, for instance, might automate information acquisition and analysis almost completely, gathering and scoring transactions at a scale no human could match, while deliberately holding decision selection and action implementation at a low level of automation, so that a human chooses whether to freeze an account and initiates the action. This uneven profile is not a compromise but a design: it places heavy automation where the machine's statistical power dominates and reserves human authority for the stages where context, accountability, and the cost of error are greatest. Framing HITL as a single dial to be set somewhere between manual and autonomous misses this structure and leads to coarser designs than the functions warrant.

The ironies of automation deserve to be stated in their full force, because they undercut the intuition that automation straightforwardly reduces the demands on the human. As automation handles more of the routine, two things happen at once: the human's manual skills, exercised less often, decay; and the situations that remain for the human are, by selection, the ones the designers judged too difficult or unusual to automate. The operator is thus progressively deskilled precisely as the residual task grows harder, and is expected to step in, cold, at the moment of greatest difficulty. This is not a transitional problem to be solved by better training alone; it is a structural consequence of the division of labor that automation creates, and it means that preserving human competence must be treated as an active design objective rather than an assumed constant. Every subsequent section of this paper can be read as an attempt to design around, rather than wish away, this irony. Contributions on semiconductor, RF/MEMS and microelectronic systems engineering and biomedical imaging inform the framing adopted here [64]–[68]. Cognate work addressing cybersecurity, data governance, and IT-risk management provides complementary grounding [69]–[89]. A related stream of research on internal audit, risk governance, and financial-sector controls reinforces these observations [90]–[100].

3. Advances and the State of the Art

3.1 Interaction paradigms and active learning

A first stream of advance concerns how humans efficiently shape models. Active learning addresses the cost of labeled data by letting the model query a human oracle for labels on the instances expected to be most informative, typically those about which it is most uncertain or that most reduce expected error [60]. By concentrating human effort where it has the greatest marginal value, active learning can reach target accuracy with substantially fewer labels than random sampling, making it a foundational HITL mechanism.

Active learning also carries a subtlety that tempers its appeal and illustrates a general HITL lesson: optimizing the machine's needs is not the same as optimizing the joint system. Querying the human on the instances the model finds most uncertain concentrates effort on precisely the borderline, ambiguous cases that humans also find hardest and label least reliably. The samples most informative to the model are thus often the ones on which human judgment is noisiest, so a naïve uncertainty-sampling strategy can amplify labeling error even as it accelerates convergence. Effective active learning must therefore weigh not only the information a query would yield but the reliability of the answer it is likely to receive, and this tension, between what would most help the machine and what the human can actually provide well, recurs throughout HITL design.

Interactive machine learning generalizes this idea from labeling to a tight, rapid loop in which people inspect model behavior and provide feedback (corrections, feature guidance, constraints) observing the effects quickly enough to steer the model iteratively [1]. Here the human is not a passive label source but an active collaborator who brings domain knowledge to bear. This reframing carry design implications: the interface must expose model state legibly, respond fast enough to sustain a sense of agency, and tolerate imperfect and evolving human input.

The demand for a tight loop is more than an ergonomic nicety; it changes what the human can contribute. When feedback produces a visible effect within seconds, the person can form and test hypotheses about how the model behaves, building an accurate mental model of its competence and steering it with intent. When the loop is slow, when a correction disappears into an overnight retraining job whose effects are diffuse and delayed, the person cannot connect action to consequence, the sense of agency dissolves, and the interaction degrades into blind labeling. Latency, in other words, is not merely a performance metric but a determinant of the quality of human contribution, and this places real constraints on the model and infrastructure choices that underlie an interactive system. A tension follows: the most powerful models are often the slowest to update, so interactive machine learning frequently trades some raw model capacity for the responsiveness that makes genuine collaboration possible.

Alongside these mechanisms, a body of empirical guidance has consolidated into design principles for human–AI interaction. Amershi et al. [101] synthesize prior work into eighteen validated guidelines spanning initial expectation-setting, behavior during interaction, handling of errors, and adaptation over time. Such guidelines mark a maturation of the field from bespoke systems toward reusable, evaluated design knowledge, an essential step for HITL to scale beyond individual applications.

3.2 Explanation and calibrated trust

A second stream concerns the informational basis for appropriate reliance. For a human to add value, they must know when to accept and when to question a model's output, which requires insight into how the model reached its conclusion and how confident it should be. Explainable AI (XAI) has grown into a broad field offering post-hoc and intrinsic techniques (feature attributions, counterfactuals, example-based explanations, and interpretable models) surveyed and taxonomized in works such as Guidotti et al. [102] and Arrieta et al. [103]. These methods give HITL systems a vocabulary for exposing model reasoning to human overseers.

Explanation is a means, not an end; the end is calibrated trust. Lee and See [104] argue that the objective is appropriate reliance, trust matched to the automation's actual capabilities, rather than maximal trust. Over-trust yields misuse and automation bias; under-trust yields disuse and forfeited benefit. Explanations, uncertainty estimates, and performance feedback are instruments for calibrating trust to reality. Importantly, evidence shows that explanations do not automatically improve decisions: poorly designed or persuasive-but-uninformative explanations can inflate confidence without improving accuracy, a phenomenon of over-reliance documented in human–AI decision-making studies [105]. Effective HITL explanation must therefore be evaluated by its effect on joint decision quality, not by its plausibility to users.

The distinction between an explanation that persuades and one that informs is the crux of the matter, and it is more slippery than it first appears. An explanation that makes a recommendation feel intelligible tends to increase the human's confidence in it regardless of whether the recommendation is correct, because plausibility and correctness are psychologically conflated. A fluent rationale for a wrong answer is therefore worse than no rationale at all: it converts a case the human might have questioned into one they accept. This is why the behavioral standard matters so much. The question to ask of an explanation is not “does it help users understand the model’s reasoning?” but “does it help users accept the model when it is right and reject it when it is wrong?”, and evidence suggests that many explanations that pass the first test fail the second, raising confidence uniformly rather than selectively.

Calibrated trust also has a temporal and relational dimension that a single-decision framing misses. Trust is built and revised through a history of interactions; a model that errs conspicuously early can forfeit reliance it deserves, while one that succeeds through a long benign stretch can accumulate reliance it has not earned for the harder cases to come. Communicating not just a recommendation but the model’s competence boundaries, the regions of the input space where it is reliable and those where it is not, is therefore central, because appropriate reliance is case-specific: the same model may warrant near-complete trust on typical cases and near-complete skepticism on atypical ones. An explanation regime that conveys a single global impression of trustworthiness, rather than this case-by-case texture, cannot support the discriminating reliance that HITL requires.

3.3 Task allocation, mixed-initiative, and adaptive autonomy

A third-stream concern who does what, and when. Static allocation, fixing in advance which functions the machine performs and which the human performs, is often suboptimal because the ideal division depends on context, workload, and case difficulty. Mixed-initiative interaction offers a more fluid model in which human and system opportunistically take the lead depending on who is better positioned to act, with the system reasoning about the expected value of intervening and the cost of interrupting the user [106]. This principle underpins designs in which a model handles routine cases autonomously but escalates uncertain or high-stakes cases to a human, and in which the level of automation itself adapts to conditions.

Adaptive and adjustable autonomy extend this idea by allowing the degree of automation to change dynamically, raised when the operator is overloaded or the model is confident, lowered when situations are novel or stakes are high. Deciding when to defer is itself a learnable problem: research on learning to defer and on complementary team design trains models not merely to predict but to decide whether to predict or route a case to a human, optimizing the performance of the human–model team rather than the model alone [107]. This reframing, optimizing the team objective, represents one of the most consequential recent shifts in HITL research.

The learning-to-defer formulation is powerful precisely because it makes the model’s decision to abstain a first-class object of optimization rather than a fixed threshold applied after the fact. A model trained to maximize its own accuracy will be reluctant to abstain on cases it can answer at all, whereas a model trained to maximize team accuracy will learn to defer whenever the human is expected to do better, even on cases the model could answer with moderate confidence. The two objectives diverge most sharply exactly where it matters, on the difficult residual, and the shift from the first to the second is what allows a system to allocate cases by comparative advantage rather than by model confidence alone. This is a genuine conceptual advance, because it turns the allocation of authority from a static engineering parameter into a learned policy responsive to the respective strengths of human and model.

Yet the formulation also exposes how much these systems must assume about the human to work. To decide whether to defer, the model needs an estimate of how well the human will do on the case in question, and that estimate is itself a model (of a particular person, on a particular day, under a particular workload) that may be wrong, may be unfair across different operators, and may drift as the human's skill and fatigue change. A deferral policy trained against an idealized or averaged human can misroute systematically, handing cases to a human who is in fact worse on them or withholding cases from a human who would have caught the model's error. The promise of learnable allocation is thus inseparable from the difficulty of modeling the human accurately, and this difficulty (rather than the machine-learning machinery, which is comparatively well understood) is where the hard problems lie.

3.4 Domain applications

Finance and business analytics. In credit scoring, fraud detection, and investment analytics, models process volumes and dimensionalities beyond human reach, yet regulation, fairness obligations, and tail risk keep humans in decision loops. A common pattern is model-scores-plus-analyst-review, in which the model ranks or flags cases and analysts adjudicate marginal or high-value ones. Regulatory expectations for explanation, such as adverse-action reasons and demands for meaningful human oversight of automated decisions, make XAI and clear escalation paths operational necessities rather than optional features. The challenge is designing review so that analysts genuinely add discernment rather than rubber-stamping model output under time pressure. The financial setting sharpens a tension between two functions the human is asked to serve. In one role the analyst is a source of additional accuracy, catching the model's errors on complex or unusual cases. In another the analyst is a source of legitimacy and legal defensibility, providing the "meaningful human oversight" that regulation increasingly demands regardless of whether that oversight measurably improves accuracy. These roles can conflict: a review process optimized for throughput and audit compliance may produce documented human sign-off on thousands of decisions while adding no real discernment, satisfying the letter of oversight requirements while hollowing out their intent. The financial domain, with its dense regulatory apparatus and its acute cost pressures, is where this gap between nominal and substantive oversight is most visible, and where the temptation to treat the human as a compliance artifact rather than a decision-maker is strongest. Tail risk gives the finance case a further distinctive character. Much of the value of human involvement in financial decisions lies not in the routine but in the rare, correlated, high-consequence event, the fraud pattern the model has never seen, the market regime shift that invalidates its training distribution, where statistical models are structurally weakest because such events are underrepresented in any historical sample. Here the human's contextual and causal reasoning, and their capacity to recognize that the world has changed in a way the data cannot yet reflect, are the point of keeping them in the loop. A HITL design in finance that optimizes only for average-case performance will tend to erode exactly the human capacities most needed when the average case ceases to apply.

Public services and digital government. Governments increasingly use algorithmic tools for eligibility screening, resource prioritization, and fraud detection in benefits and taxation. Here HITL carries heightened normative weight: decisions affect rights and access to essential services, populations are heterogeneous, and legitimacy depends on contestability and due process. High-profile failures of insufficiently supervised automated systems in the public sector have underscored the risks of removing meaningful human judgment [108]. Effective public-sector HITL emphasizes not only accuracy but transparency, the ability of affected individuals to contest decisions, and caseworker discretion informed, rather than displaced, by algorithmic recommendation.

What distinguishes the public-sector case is that the affected individual is a party to the decision with rights, not merely a data point to be classified, and this changes the standard against which the system must be judged. A model that is accurate in aggregate can still be unacceptable if it errs systematically against a vulnerable subgroup, if its errors are effectively uncontestable, or if it renders decisions whose basis cannot be explained to those they affect. The legitimacy of a public decision rests on process as much as outcome, on the person's ability to understand why, to be heard, and to have a mistake corrected, and these procedural goods are precisely what opaque automation tends to erode. HITL in government is therefore not primarily an accuracy-improvement strategy but a mechanism for preserving the procedural rights that distinguish administrative decisions from mere predictions.

The public-sector experience also illustrates a specific failure of oversight that is easy to overlook: automation can quietly narrow the discretion that caseworkers use to handle the edge cases and hardships that formal rules cannot anticipate. When a recommendation is presented as authoritative, when overriding it requires justification while accepting it does not, and when caseworkers are evaluated on conformance, the practical effect is to convert a discretionary judgment into a rubber stamp, even where the formal policy preserves the caseworker's authority. The human remains in the loop on paper while the substance of their judgment is squeezed out by the asymmetry of effort and accountability between accepting and challenging the machine. Guarding against this requires attention not only to the model and the interface but to the incentives and procedures surrounding their use.

Risk and security operations. In cybersecurity and operational resilience, HITL is pervasive: intrusion-detection and alert-triage systems generate more signals than analysts can examine, so models prioritize and cluster alerts while analysts investigate and decide on response. The dominant pain point is the base-rate problem, rare true positives amid overwhelming benign traffic, which produces alert fatigue and desensitization, a security-specific manifestation of vigilance decrement [109]. Here the value of HITL design lies in ranking, contextualizing, and summarizing to preserve scarce analyst attention for genuine threats, and in feeding analyst dispositions back to improve the model. Security operations expose the base-rate problem in an especially unforgiving form, and it is worth being explicit about its logic. When genuine threats are vanishingly rare relative to benign activity, even a detector with an excellent false-positive rate generates, in absolute terms, far more false alarms than true ones, because the small error rate is multiplied by an enormous volume of benign events. The analyst's daily experience is therefore dominated by false positives, and the rational, fatigue-driven adaptation, learning to dismiss alerts quickly, directly undermines the vigilance the role depends on. This is not a failure of individual diligence but a predictable response to a signal environment engineered, inadvertently, to punish attention. HITL design that merely adds more alerts, however accurate each is, worsens the problem; the useful designs are those that reduce the volume reaching the human through clustering, deduplication, and contextual enrichment, so that scarce attention is spent on genuinely distinct and consequential events. The adversarial character of security also gives HITL a dimension absent from the other domains: the environment contains an intelligent opponent who adapts to the defense. A human analyst's judgment is valuable here partly because adversaries specifically design their behavior to evade the patterns that automated detectors have learned, and the human's capacity to reason about novel, deliberately disguised activity is a hedge against an opponent optimizing against the model. This argues against high-autonomy configurations that remove the human's situational awareness, because an adversary who understands that responses are automated can weaponize that automation, triggering costly automated reactions deliberately, or hiding in the blind spots the automation creates. Feeding analyst dispositions back into the model helps the defense adapt in turn, but the loop must be designed with the awareness that the data it learns from is being shaped by an opponent who would like nothing better than to teach it the wrong lessons.

3.5 A taxonomy of HITL patterns (described table)

The applications above instantiate a small number of recurring patterns, which we organize along two dimensions: the **timing** of human involvement (pre-deployment, in-operation, post-hoc) and the **locus of authority** (whether the human trains, supervises, is supervised by, or collaborates with the automation). We describe the resulting taxonomy as a conceptual table with five principal patterns.

- **Human-as-teacher (pre-deployment, human shapes model).** People supply labels, corrections, features, and constraints. Active learning and interactive machine learning are the canonical mechanisms. Value derives from efficient elicitation of human knowledge; the key risk is annotation bias and inconsistency propagating into the model.
- **Human-as-reviewer / human-on-the-loop (in-operation, human supervises).** The model proposes and acts, or proposes and waits, while a human monitor and can override. Analyst review of flagged transactions and caseworker sign-off exemplify this. Value derives from a safety net for model error; the key risks are automation bias and rubber-stamping.
- **Machine-as-adviser / human decides (in-operation, human is decision-maker).** The model recommends and the human selects, retaining authority. Classic decision support and clinical or credit recommendation sit here. Value derives from augmenting human judgment; the key risk is algorithm aversion or, conversely, uncritical acceptance.
- **Escalation / learning-to-defer (in-operation, dynamic allocation).** The model handles confident cases autonomously and routes uncertain or high-stakes ones to humans, with the deferral policy potentially learned. Value derives from optimizing the human–model team and conserving attention; the key risk is miscalibrated deferral that either overloads humans or hands them only the hardest cases without support.
- **Human-as-auditor / contestation (post-hoc, human corrects).** People audit outcomes, handle appeals, and feed corrections back for retraining. Value derives from accountability, redress, and continual improvement; the key risk is that feedback loops entrench past errors if corrections are unrepresentative.

These patterns are not mutually exclusive; mature systems combine several across the decision lifecycle. The taxonomy's purpose is diagnostic: naming a pattern makes its characteristic risks and evaluation needs explicit, and it clarifies which advances from Section 3 apply.

Contributions on enterprise IT systems, cloud migration, and service management inform the framing adopted here [110]–[122]. Cognate work addressing technology law, AI governance, and regulatory compliance provides complementary grounding [123]–[127]. A related stream of research on financial analytics, planning, and enterprise decision systems reinforces these observations [128]–[142].

4. Open Challenges

4.1 Automation bias and algorithm aversion

The two dominant failure modes of human–machine reliance pull in opposite directions. Automation bias is the tendency to over-rely on automated cues, accepting incorrect recommendations and failing to act on contradictory evidence; it produces both errors of commission (following bad advice) and omission (missing events the automation did not flag) [143], [144]. It is exacerbated precisely by the conditions HITL is meant to address, high workload, time pressure, and long stretches of reliable automation that breed complacency. In the opposite direction, algorithm aversion describes people discounting or abandoning algorithmic advice, especially after seeing the algorithm err, even when it outperforms them; notably, this aversion can be reduced when people are given even slight ability to adjust the algorithm's output [145], [146]. That the same system can elicit both over- and under-reliance, sometimes from different users or at different times, is the central difficulty of HITL design. It means neither "trust the machine" nor "trust the human" is a sound default; the goal must be calibrated, case-by-case reliance, which is far harder to engineer and to sustain.

The two biases are not merely opposite errors to be balanced; they interact in ways that make simple correctives counterproductive. A design change intended to reduce automation bias, say, by making the model's recommendations less prominent or by requiring the human to justify acceptance, may tip susceptible users into algorithm aversion, causing them to discard advice that was, on balance, worth taking. Conversely, measures that build trust to overcome aversion, such as emphasizing the model's strong track record, can seed the complacency that produces automation bias. Because different users sit at different points on this spectrum, and because the same user moves along it with fatigue, workload, and accumulated experience, no single static design setting is correct for everyone at all times. This is the deeper reason the field's goal must be calibration rather than the promotion or suppression of trust in general: the target is not a level of reliance but a correspondence between reliance and reliability, case by case.

The finding that even a slight ability to modify an algorithm's output can restore willingness to use it is worth dwelling on, because it points to agency, rather than accuracy, as a lever on reliance. People appear to accept imperfect algorithms more readily when they retain some control over the result, which suggests that the felt experience of authorship and control shapes reliance independently of the model's demonstrated performance. This has a constructive implication for design, preserving a meaningful margin of human adjustment may improve adoption of beneficial models, but also a cautionary one, since the same mechanism could induce acceptance of a model on the basis of a psychological sense of control rather than a warranted assessment of its reliability. Agency, like explanation, is a double-edged instrument that can produce either appropriate or inappropriate reliance depending on how it is deployed.

4.2 Cognitive load, vigilance, and skill degradation

Placing a human in a supervisory role imposes real cognitive costs. Sustained monitoring of a mostly reliable automated process produces vigilance decrement, declining detection of rare events over time, a robust finding from attention research directly relevant to alert triage and fraud review. Reviewing model output with explanations adds interpretive load that, under time pressure, may be shed in favor of heuristic acceptance. Over longer horizons, reliance on automation can erode the very expertise humans are retained to provide, hollowing out the skills needed when they must intervene [4]. Designing HITL work so that human engagement remains meaningful, manageable, and skill-preserving is an unresolved sociotechnical problem, not merely an interface question.

These costs compound one another in a way that a static account of workload misses. Explanation, offered as a remedy for opaque recommendations, is itself a demand on attention, and under the very time pressure that makes support most necessary it is the first thing to be discarded: the rational shortcut for an overloaded reviewer is to skip the explanation and accept the recommendation, which is precisely the behavior explanation was meant to prevent. There is thus a perverse dynamic in which the interpretive aids that would enable good decisions are affordable only when the stakes are low, and are shed exactly when they matter most. Designing for realistic rather than idealized attention, assuming a tired reviewer at the end of a long shift rather than an alert one at its start, is a discipline the field has been slow to adopt.

Skill degradation deserves particular emphasis because its costs are deferred and therefore easy to discount. An organization that automates the routine and retains humans only for the exceptions enjoys immediate efficiency gains while its human expertise silently atrophies, and the bill arrives only when a situation exceeds the automation's competence and the humans, out of practice, prove unable to take over. This temporal separation between benefit and cost systematically biases organizational decisions toward more automation than is prudent, because the efficiency is visible on this quarter's ledger while the erosion of capability is not. Treating the maintenance of human skill as a cost of running an automated system (provisioning for practice, rotation through unautomated cases, and deliberate exercise of judgment) runs against the grain of the efficiency logic that motivates automation in the first place, which is why it is so often neglected.

4.3 Accountability and the moral crumple zone

When a human and a machine jointly produce a decision, responsibility can become diffuse. A recurring hazard is the "moral crumple zone," in which a human operator absorbs blame for failures of a larger automated system they had limited real capacity to prevent, nominally in control, practically unable to override effectively [147]. Superficial human oversight can thus launder algorithmic decisions with a veneer of accountability while providing none in substance. Meaningful human control requires that the person have genuine authority, adequate information, sufficient time, and real alternatives, conditions frequently absent in production systems optimized for throughput. Aligning formal accountability with actual capacity to intervene is a governance challenge that technical design alone cannot resolve.

The moral crumple zone is insidious because it can arise from designs that appear, on their face, to strengthen accountability. Requiring a human sign-off on every automated decision seems to place responsibility squarely on a person, but if that person cannot realistically evaluate the volume of decisions they are asked to approve, the requirement does not create accountability so much as relocate blame. The system as a whole makes the decisions; the human absorbs the liability for its failures. This produces a doubly perverse outcome: the individuals held responsible are those least able to have prevented the harm, while the designers and deploying organizations, whose choices actually shaped the outcomes, are shielded by the presence of a nominal human decision-maker. Accountability, properly understood, has to track the real locus of control, and a HITL arrangement that severs the two is worse than honest automation because it obscures where responsibility truly lies. The remedy cannot be purely technical, but neither is it purely a matter of policy, because the conditions for meaningful control are partly design decisions. Whether the human has adequate information depends on what the interface surfaces; whether they have sufficient time depends on how throughput targets are set; whether they have real alternatives depends on whether the system makes overriding as easy and as defensible as acceding. Each of these is a lever that designer's control, which means the distribution of accountability is, in part, engineered rather than given. Recognizing this reframes accountability from a question to be settled after a failure into a set of requirements to be built in beforehand, a stance that Section 5 develops into an argument for operationalizing meaningful human control as verifiable design criteria.

4.4 Evaluation of joint systems

Perhaps the most consequential gap is methodological. HITL systems are routinely evaluated by the accuracy of the model in isolation, yet the quantity that matters is the performance of the human–machine team, which can diverge sharply from model accuracy: a more accurate model can yield worse joint decisions if it induces over-reliance, and explanations that look helpful can degrade outcomes [105]. Measuring complementarity, whether the team beats both the best human and the best model, requires studies with real users, realistic tasks, and appropriate baselines, which are costly and comparatively rare. Metrics for calibrated reliance, appropriate override behavior, and long-term effects on skill and trust are still immature. Without evaluation aimed at the joint system, the field risks optimizing components while the whole underperforms.

The divergence between model accuracy and team accuracy is not an occasional anomaly but a structural feature, and appreciating why clarifies what evaluation must capture. The team's performance depends jointly on the model's accuracy, the human's accuracy, and, decisively, on the human's ability to tell, case by case, which of them to trust. A model improvement that raises accuracy while degrading the human's ability to discriminate its errors can lower team performance; an explanation that raises confidence uniformly rather than selectively can do the same. What determines the outcome is the interaction between the components, and interactions are precisely what component-level evaluation cannot see. This is why a system can be assembled entirely from parts that each test well and still fail as a whole, and why the field's habit of reporting model metrics as though they predicted deployed performance is not merely incomplete but potentially misleading. Rigorous joint evaluation is hard for reasons that go beyond expense. It requires representative users rather than convenient proxies, because expertise and domain familiarity strongly shape reliance behavior; realistic tasks and incentives, because people behave differently when consequences are real; and appropriate baselines, the best unaided human and the best unaided model, without which a claim of complementarity is unfalsifiable. It also requires time, because the effects that most threaten HITL systems, such as complacency, trust drift, and skill decay, emerge only over weeks and months and are invisible to the short-controlled studies that dominate the literature. The gap between what is easy to measure and what matters to measure is, in this domain, unusually wide, and closing it is less a matter of cleverer metrics than of a willingness to bear the cost of studying the joint system as it actually operates over time.

Contributions on predictive analytics and data-driven decision-support systems inform the framing adopted here [148]–[157]. Cognate work addressing enterprise cybersecurity and cyber-defense engineering provides complementary grounding [158]–[169]. A related stream of research on enterprise IT service delivery and security operations reinforces these observations [170]–[172].

5. Future Opportunities and Research Agenda

5.1 From accuracy to calibrated reliance

The foundational shift the field must complete is to make the human–machine team the unit of optimization and evaluation. This entails developing and standardizing metrics for appropriate reliance, rates of correct acceptance and correct override, trust calibration relative to case-level reliability, and complementary performance gains over both parties alone [104], [105]. Benchmarks and reporting norms that require joint-system evaluation with human participants, analogous to established norms for model benchmarking, would accelerate cumulative progress and discourage the deployment of components that look strong in isolation but weaken the team.

Concretely, appropriate reliance can be decomposed into behaviors that are separately measurable and separately optimizable. A team can be characterized by how often the human correctly accepts a right recommendation, correctly rejects a wrong one, wrongly overrides a right one, and wrongly accepts a wrong one, and the last two, the reliance errors, are the ones that component metrics never expose. Reporting these quantities, rather than collapsing everything into a single accuracy figure, would let designers see whether a change improves the team by improving the model or by improving the human's discrimination, which are different achievements with different implications. It would also make visible the failure mode in which a more accurate model produces a less discriminating human, a trade-off that aggregate accuracy actively conceals. Establishing such reporting as a norm is a modest-seeming intervention with large consequences, because what a field measures is what it learns to improve.

5.2 Adaptive and learnable task allocation

Learning-to-defer and complementary-team formulations should be extended from binary defer-or-not decisions toward richer, context-sensitive allocation that accounts for individual human strengths, current workload, and the changing cost of errors [107]. Promising directions include policies that route cases to the specific human best suited to them, that adapt automation levels to measured operator state, and that explicitly balance conserving attention against avoiding overload. Because such policies wield real authority over people's work, they must themselves be transparent and contestable, raising a second-order HITL question: keeping humans meaningfully in control of the allocation mechanism, not only of individual cases.

5.3 Human-centered and actionable explanation

XAI should be reoriented from technique-driven faithfulness metrics toward demonstrated improvement in joint decision quality for real tasks and users. This means designing explanations that support appropriate reliance, conveying uncertainty and the boundaries of competence, surfacing when a case lies outside the model's reliable range, and enabling verification rather than mere persuasion [103], [105]. Uncertainty communication, example- and counterfactual-based explanation tailored to decision context, and interfaces that prompt reflection rather than reflexive acceptance are priorities. The evaluative standard should be behavioral: does the explanation help people accept good advice and reject bad advice?

5.4 Sociotechnical accountability and meaningful human control

Realizing accountable HITL requires integrating technical design with governance. Research should operationalize meaningful human control into verifiable design requirements (sufficient information, time, authority, and viable alternatives) and develop audit methods that test whether oversight is substantive rather than nominal, guarding against moral crumple zones [147]. This connects to emerging regulatory demands for human oversight of automated decisions, and offers an opportunity to translate legal principles into concrete, testable interaction patterns for finance and public services, where contestability and due process are paramount [108].

The value of turning meaningful human control into verifiable criteria is that it converts an aspiration that is easy to claim into a property that can be tested and, if absent, falsified. One can ask whether reviewers are in fact given the information needed to evaluate a recommendation, whether the pace of work leaves time to exercise judgment, whether overriding the model is as procedurally supported as accepting it, and whether alternatives to the recommended action genuinely exist. Each question admits an empirical answer, and a system that fails any of them is providing the form of oversight without its substance regardless of what its documentation asserts. Developing standardized audits around such criteria would give regulators, deploying organizations, and affected parties a shared and defensible basis for judging whether a claim of human oversight is real. This reframes governance from a matter of after-the-fact blame allocation to one of before-the-fact design verification, aligning the incentives of builders with the substantive control the principle is meant to guarantee.

5.5 Rigorous, mixed-methods evaluation and longitudinal study

Finally, the field needs methodological investment. Short controlled studies capture immediate reliance but miss the dynamics that matter most (complacency, skill decay, and trust drift) which unfold over weeks and months. Longitudinal and field studies, combined with qualitative inquiry into how practitioners actually use these systems, are essential to understand HITL in situ. Standardized tasks, shared datasets with human decisions, and reusable evaluation protocols would lower the cost of such work and make findings comparable across studies and domains, building the cumulative evidence base the field currently lacks.

Contributions on artificial intelligence in education, learning, and digital health inform the framing adopted here [173]–[178]. Cognate work addressing financial analytics, audit, IT-risk and governance across the wider research portfolio provides complementary grounding [179]–[350]. A related stream of research on the foundational and directly cited literature underpinning the present study reinforces these observations [1]–[5], [60]–[63], [101]–[109], [143]–[147].

6. Conclusion

Human-in-the-loop decision systems are the practical answer to a durable tension: organizations want the scale and consistency of automation but cannot, for legal, ethical, and epistemic reasons, cede consequential decisions entirely to opaque models. This paper has argued that the promise of HITL, complementary human and machine strengths, is real but not automatic. Realizing it requires designing the interaction so that the joint system genuinely outperforms either party alone, a goal frustrated by automation bias, algorithm aversion, cognitive load, diffuse accountability, and evaluation practices that measure the model rather than the team.

The advances we surveyed, active learning and interactive machine learning, explainable AI and trust calibration, mixed-initiative and learning-to-defer allocation, and hard-won domain experience in finance, public services, and security, supply a rich toolkit. What ties them together, and what we advance as the central design principle, is to treat the human and the model as a single joint cognitive system. Under that principle, the right questions become how to allocate authority adaptively, how to explain in ways that produce calibrated reliance, how to preserve meaningful human control and accountability, and how to evaluate the team as a whole. The research agenda we have proposed (calibrated-reliance metrics, learnable allocation, human-centered explanation, sociotechnical accountability, and rigorous longitudinal evaluation) follows directly. Pursued together, these directions can move HITL from an intuitively appealing compromise to an engineering discipline for building decision systems that are more capable, more trustworthy, and more accountable than either humans or machines acting alone.

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