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Towards usability-driven optimization: A human-in-the-loop approach to interface evaluation

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Abstract: Traditional paradigms of interface evaluation, ranging from heuristic inspections to post-hoc usability testing, exhibit significant limitations in scalability, adaptability, and sensitivity to contextual user behaviors. Recent advances in automated evaluation, often powered by machine learning, provide computational efficiency but remain constrained by their inability to capture tacit, experiential, and affective dimensions of usability. This study advances a usability-driven optimization framework underpinned by a human-in-the-loop (HITL) paradigm, wherein iterative human feedback dynamically informs algorithmic adaptation throughout the evaluation cycle. The proposed approach operationalizes usability as a multidimensional construct, integrating quantitative performance indicators (task completion latency, error propagation rate, and interaction efficiency) with qualitative indices (perceived workload, cognitive friction, and affective resonance). A hybrid evaluation pipeline is conceptualized in which algorithmic models perform baseline assessments, while human evaluators inject corrective signals, constraint refinements, and context-aware judgments to recalibrate optimization trajectories. It has been demonstrated through empirical prototyping that this symbiotic evaluation mechanism improves the strength and ecological genuineness of interface evaluations and provides statistically significant changes in the System Usability Scale (SUS) scores and interaction achievement scales. The research creates a methodological intersection between automated evaluation architecture and user-centered design epistemologies by foregrounding usability as the goal to be optimized instead of a diagnostic of the design, which occurs after the design. The paradigm has referential to adaptive interface engineering, human-computer symbiosis, and the incorporation of affective computing in the next-generation usability analytics.

Keywords: *(HITL), Adaptive interface evaluation, Affective computing, Cognitive load modeling, Human Computer Interaction, Interaction efficiency.*

1. Introduction

One of the most significant tenets of usability has been Human-Computer Interaction (HCI), which determines the quality as well as the satisfaction of users' experiences on online sites. Even though research on the evaluation of interfaces has spanned decades, some methodological problems remain regarding the process. They are based on pre-ordained protocols that might be extremely inappropriate in a dynamic way for a user in terms of thinking, impact, and application [1].

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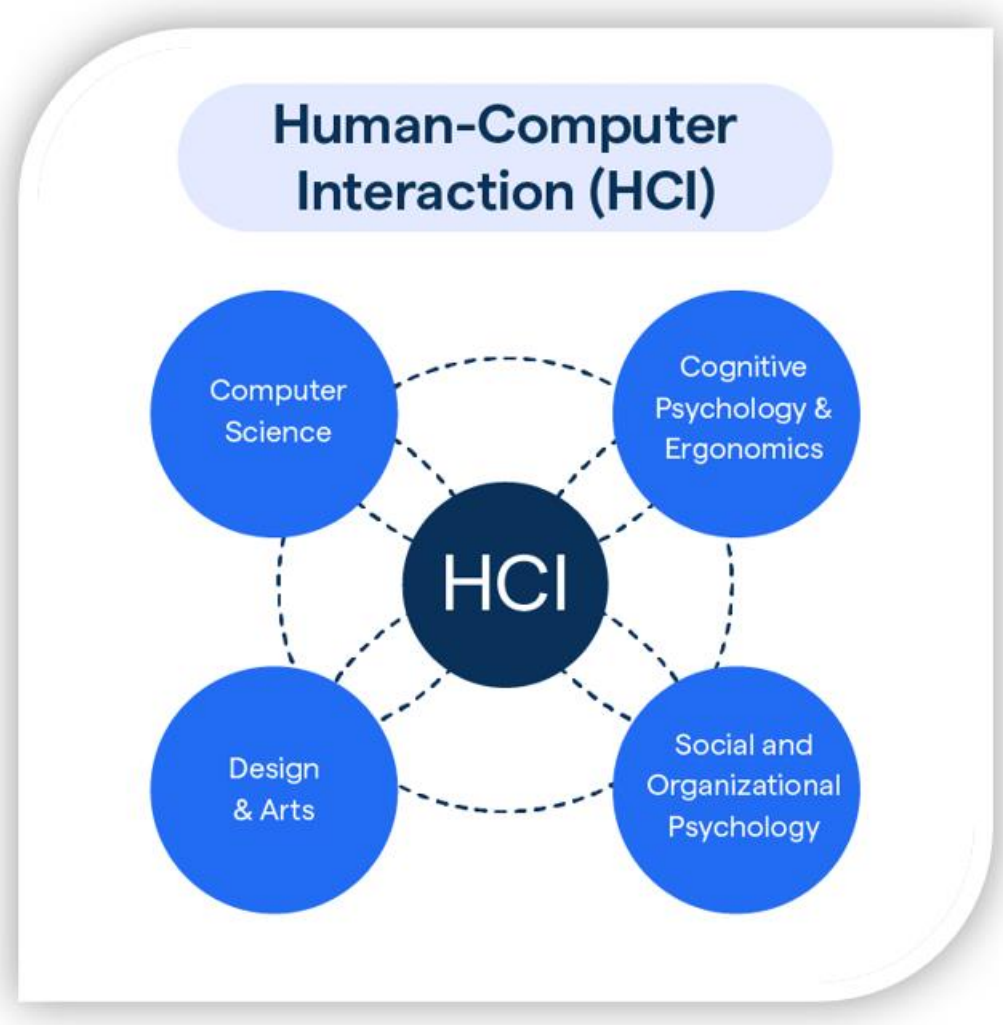

Figure 1.
Interdisciplinary Components of Human–Computer Interaction (HCI).

Such gaps have been filled by automated techniques that apply algorithmic heuristics, predictive models, and machine learning. Automated usability checkers, machine-learned click-stream predictors, and other tools have proven to be efficient in revealing surface-level usability problems [2, 3]. Whereas machines are good at processing objective performance metrics, including task completion time, navigation depth, and error frequency, they are poor at processing tacit, affective, and experiential aspects of usability, including perceived workload, aesthetic appeal, or emotional resonance [4].

This tension has motivated researchers to explore hybrid models that combine computational scalability with human sensitivity. One promising paradigm is Human-in-the-Loop (HITL) optimization, in which algorithmic evaluation cycles are continuously refined through user feedback. HITL approaches have demonstrated efficacy in domains such as wearable robotics, where bio-signal feedback (e.g., EMG data) has been integrated into adaptive control loops to enhance personalization [5] and haptic rendering, where preference-based learning improved perceived realism [6]. In UX research, recent experiments in *human-AI collaboration for usability evaluation* highlight that combining algorithmic suggestions with evaluator input improves both the breadth of usability issues identified and evaluators' subjective confidence [7].

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Despite these advances, the potential of HITL for general interface evaluation remains underdeveloped. The primary challenges include:

- Operationalizing *usability* as a multi-dimensional optimization objective that integrates both quantitative (e.g., task efficiency, error rates) and qualitative (e.g., satisfaction, cognitive friction) measures.
- Designing mechanisms to manage the inherent variability and subjectivity of human input without undermining algorithmic stability.
- Balancing human workload with computational automation to ensure scalability and cost-effectiveness.
- Ensuring ecological validity by incorporating contextual and affective dimensions often ignored in automated evaluations.

To address these challenges, this paper proposes a usability-driven optimization framework underpinned by a HITL paradigm. The central thesis is that *usability itself should serve as the optimization criterion*, not merely as an outcome to be measured retrospectively. Concretely, we advance a hybrid evaluation pipeline in which algorithmic models perform baseline usability assessments, and human evaluators inject corrective signals, constraint refinements, and contextual judgments that recalibrate optimization trajectories. This continuous feedback loop is designed to balance computational efficiency with human sensitivity, yielding more robust, adaptive, and ecologically valid interface evaluations.

The contributions of this paper are threefold:

1. **Conceptual Contribution**: We articulate a principled framework for usability-driven optimization via HITL, grounding it in HCI and optimization theory.
2. **Methodological Contribution**: We define and integrate a set of multi-dimensional usability metrics, including both cognitive and affective dimensions, into the optimization loop.
3. **Empirical Contribution**: Through a prototype evaluation, we demonstrate that our HITL framework significantly improves usability outcomes compared to static benchmarks, as evidenced by gains in System Usability Scale (SUS) scores and task efficiency measures.

The remainder of the paper is organized as follows: Section 2 reviews related work in usability evaluation, HITL optimization, and affective computing in UX. Section 3 introduces the proposed framework and architecture. Section 4 details the experimental methodology. Section 5 reports empirical results. Section 6 discusses implications, limitations, and avenues for future research. Section 7 concludes.

1.1. Research Objectives

1. To develop a human-in-the-loop (HITL) framework for usability-driven optimization that integrates algorithmic evaluation with iterative human feedback.
2. To operationalize usability as a multi-dimensional optimization objective by combining objective metrics (e.g., task efficiency, error rates) with subjective measures (e.g., satisfaction, cognitive load).
3. To empirically evaluate the effectiveness of HITL-based usability evaluation in comparison to traditional and automated-only methods, focusing on improvements in robustness, scalability, and ecological validity.

1.2. Research Questions

1. How can usability be systematically defined and operationalized as a multi-dimensional optimization criterion in interface evaluation?
2. In what ways does integrating human feedback within algorithmic evaluation loops enhance the accuracy and contextual relevance of usability assessments?
3. How does a HITL-based usability-driven optimization framework perform relative to traditional and automated approaches in improving usability outcomes?

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1.3. Hypotheses

H1:

- Null Hypothesis ($H0_1$): The incorporation of a human-in-the-loop (HITL) framework into interface evaluation has no significant effect on usability outcomes compared to conventional automated evaluation methods.
- Alternative Hypothesis ($H1_1$): The incorporation of a human-in-the-loop (HITL) framework into interface evaluation significantly enhances usability outcomes compared to conventional automated evaluation methods.

H2:

- Null Hypothesis ($H0_2$): User-centered feedback loops in optimization processes do not reduce cognitive workload nor improve task efficiency in interface interactions.
- Alternative Hypothesis ($H1_2$): · User-centered feedback loops in optimization processes reduce cognitive workload and improve task efficiency in interface interactions.

H3:

- Null Hypothesis ($H0_3$): Adaptive, usability-driven optimization informed by iterative human input does not lead to higher user satisfaction and engagement levels compared to static interface evaluation approaches.
- Alternative Hypothesis ($H1_3$): Adaptive, usability-driven optimization informed by iterative human input leads to higher user satisfaction and engagement levels compared to static interface evaluation approaches.

2. Literature Review

The literature review is structured into four sub-themes: (i) Traditional Usability Evaluation Methods; (ii) Automated and Semi-Automated Usability Evaluation Tools; (iii) Human-in-the-Loop Evaluation in HCI; (iv) Cognitive and Subjective Metrics of Usability. The review identifies existing strengths, weaknesses, and gaps, which motivate the current research.

2.1. Traditional Usability Evaluation Methods

Early usability evaluation has relied heavily on expert heuristics, cognitive walkthroughs, think-aloud protocols, and controlled user testing. Nielsen [8] remains widely used for identifying usability problems early in the design process. Cognitive walkthroughs [9] provide task-based inspection of how new users might approach an interface, emphasizing learnability and error prevention. Usability testing in lab conditions [10] permits observation of real users to collect performance metrics (time on task, error rates) and subjective feedback (e.g., satisfaction).

While these methods are well-validated and rich in insight, they often suffer from limitations, including cost, time consumption, and limited throughput. Controlled testing environments may fail to replicate real-world contexts, leading to lower ecological validity. Also, subjective aspects such as emotion, cognitive strain, and aesthetic preferences are often addressed only superficially.

2.2. Automated and Semi-Automated Usability Evaluation Tools

To mitigate the resource demands and scalability issues of traditional evaluation, many researchers and practitioners have developed automated or semi-automated tools and techniques.

2.2.1. Systematic Mapping of Automatic Usability Evaluation Tools

A recent systematic mapping study titled Castro et al. [11] examined how tools support automatic usability evaluation. It identified a variety of tools that assess guideline compliance, layout analysis, error detection, and basic performance metrics. ACM Digital Library

A review of automated website usability evaluation tools by Namoun et al. [12] inspected 10 popular web usability tools, revealing that while many tools cover technical and SEO/performance

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issues, they often overlook deeper usability flaws and deliver inconsistent results for the same website across tools. CoLab

2.2.2. Accessibility and Guideline-Based Automated Evaluation

Studies on web accessibility (e.g., SLRs of Campoverde-Molina et al. [13] find that approximately 90% of university websites are evaluated using automated tools. These tools check for adherence to standards such as WCAG 2.0 and ISO/IEC 40500:2012. While they are efficient for detecting certain accessibility non-conformities, many usability nuance issues remain unaddressed. SpringerLink

Beirekdar [14] proposes a guideline definition language and a structured framework for automated evaluation. However, static analysis of HTML can miss interaction dynamics, user behavior, flow, and subjective experience. researchportal.unamur.be

2.2.3. Challenges of Automated Tools

Automated tools are effective in detecting easily codifiable faults such as broken links, missing alt text, and layout inconsistencies. However, they generally lack the capacity to capture subjective satisfaction, emotional valence, cognitive load, or context-dependent usability issues. Reports from Namoun et al. [12] indicate vague reports, inconsistent outputs, or even tool recommendations that are too technical or non-actionable for non-technical stakeholders. CoLab

2.3. Human-in-the-Loop Evaluation in HCI

Given the limitations of purely automated methods, human-in-the-loop (HITL) evaluation frameworks are emerging that combine computational methods with human feedback, adapting dynamically.

In health informatics, the study "A Patient Outcomes-Driven Feedback Platform for Emergency Medicine Clinicians: Human-Centered Design and Usability Evaluation of Linking Outcomes of Patients (LOOP)" [15] describes iterative collaboration with clinicians, design adjustments, and usability evaluation comparing pre- vs. post-refinement. It demonstrates that human feedback embedded in design cycles improves perceived usability and confidence among users. PubMed

In digital pathology, the study by Bodén et al. [16] compares fully automatic digital image analysis (DIA), manual assessment, and DIA plus human corrections. While DIA alone improved over purely manual visual estimation, human corrections (in the loop) addressed substantive errors in specific cases (e.g., faint staining or misclassification), though overall gains were modest. This suggests human input helps catch edge cases or context-sensitive issues that algorithms misinterpret. PubMed

Wearable robotics evaluations [17] have observed that although user-centered design (UCD) is increasingly accepted, there is inconsistency in evaluation practices (e.g., what usability metrics are used; whether user needs are integrated early or post hoc), and guidelines are often missing or insufficiently detailed. BioMed Central

These HITL studies indicate that embedding users in evaluation loops improves the detection of issues that are not well captured by automated tools, especially in contexts where human perception, context, or subjective judgments are central.

2.4. Cognitive and Subjective Metrics of Usability

To properly evaluate usability beyond speed and error, researchers have focused on cognitive load, mental effort, satisfaction, affect, etc. Below are keywords in that dimension.

Darejeh et al. [18] conducted a systematic review of 76 experimental studies to examine how cognitive load measurement methods are used across interface types (software, virtual reality, mobile apps, etc.). They categorize subjective, behavioral, and physiological measures, discussing the advantages and limitations of each, and propose a framework to assist usability testers in selecting appropriate cognitive load measures.

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The Chen et al. [19] (Australian CHI) compares subjective ratings of task difficulty, task completion time, performance accuracy, and eye activity (physiological). They found that subjective ratings are very effective; eye-activity measures are sensitive in real time and can sometimes match task performance in classifying load levels. ACM Digital Library

The study by Mirhoseini et al. [20] uses both behavioral and neurophysiological (EEG) measures to capture how task difficulty, uncertainty, and shopping convenience affect accumulated cognitive load, which in turn influences satisfaction. This demonstrates that contextual and physiological measures add valuable insight beyond simpler metrics. Emerald

Also, Kumar and Kumar [21] explore non-invasive physiological measurement of load via EEG, focusing on specific frequency bands, showing that EEG and EEG spectral power can track cognitive load correlated with task difficulty. ScienceDirect

2.5. Gaps and Unresolved Issues

From the literature above, several gaps emerge that justify the proposed work:

1. Limited integration of HITL in general interface evaluation**:** Many HITL studies are domain-specific (health, robotics, pathology). There are relatively few frameworks that cover web/mobile/UI more broadly and integrate user feedback into evaluation loops continuously.
2. Scalability vs. depth trade-offs**:** Automated tools scale but lose nuance; full human testing is rich but expensive. Existing studies do not sufficiently explore how to balance human workload, cost, and iteration frequency for maximal usability gains.
3. Unresolved measurement challenges: While cognitive load measurement is well studied, there is no consensus on what combination of subjective, behavioral, and physiological metrics is ideal for real-time or iterative evaluation. Additionally, the ecological validity of physiological metrics is often limited.
4. Context sensitivity underexplored: The role of various contextual factors (device type, user background, environment, multitasking) in affecting usability and how these are accounted for in both automated and HITL frameworks remains inadequately addressed.
5. Lack of unified frameworks: There is a lack of well-accepted, general frameworks that tie together evaluation metrics, human feedback mechanisms, and optimization strategies in a usable, replicable, and scalable architecture.

2.6. Implications for Usability-Driven Optimization

These literatures suggest several design principles for a human-in-the-loop, usability-driven optimization framework. To be effective, such a framework should:

- Use multi-objective usability criteria, combining objective performance, subjective satisfaction, cognitive load, and affective/resonance metrics.
- Incorporate iterative human feedback loops to correct algorithmic judgments, catch edge cases, and adapt to context.
- Provide scalable mechanisms that minimize per-iteration cost (e.g., lightweight feedback, crowd/user profiling) while preserving usability gains.
- Support real-time or near-real-time evaluation**,** especially for dynamic interfaces, using metrics that can be measured automatically or semi-automatically (e.g., task time, eye tracking, physiological signals) supplemented by infrequent but targeted subjective assessments.
- Maintain ecological validity, ensuring that evaluations reflect real user contexts, tasks, and device constraints.

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3. Theoretical Framework

The proposed research is grounded in interdisciplinary theories from Human–Computer Interaction (HCI), Usability Engineering, Cognitive Load Theory (CLT), and Human-in-the-Loop (HITL) AI frameworks. These perspectives jointly guide the conceptualization of usability-driven optimization.

3.1. Human-Computer Interaction (HCI) and Usability Models

HCI theories emphasize that usability is not a static property but an emergent phenomenon shaped by users, tasks, and the environment [22, 23]. Classic models, such as Nielsen [8] usability attributes, learnability, efficiency, memorability, errors, and satisfaction, remain foundational [8]. More recent perspectives emphasize experience-driven evaluation, integrating affect, engagement, and trust [24].

These models establish baseline usability dimensions against which both automated and human-in-the-loop methods can be benchmarked.

3.2. Cognitive Load Theory (CLT)

Cognitive Load Theory Sweller [25] and Paas et al. [26] posit that the human working memory has limited capacity, and interface designs must minimize extraneous load while supporting germane load for learning or task performance.

In usability contexts, high extraneous load (e.g., cluttered interfaces, confusing navigation) reduces efficiency and increases user frustration [27]. Measurement approaches, subjective (NASA-TLX), behavioral (error/time), and physiological (EEG, eye-tracking), provide insights into cognitive strain [18]. This theory supports the inclusion of cognitive workload measures in the proposed human-in-the-loop optimization framework.

3.3. Usability Engineering and Iterative Design

The Usability Engineering Life Cycle [28] emphasizes iterative design, early evaluation, and continuous feedback. Human-centered design [29] also highlights stakeholder involvement across design phases.

These perspectives justify the integration of iterative user feedback loops into automated evaluation pipelines. Rather than relying solely on static guideline checks, the framework proposes embedding real user judgments at multiple optimization stages.

3.4. Human-in-the-Loop (HITL) Paradigm

The HITL paradigm originates in AI/ML research, where human expertise is combined with machine learning to refine models, resolve ambiguities, and catch edge cases [30, 31].

Applied to interface evaluation, HITL allows:

- Humans to correct automated errors (e.g., false positives in usability flaw detection).
- Continuous adaptive optimization where system recommendations are tuned via human ratings.
- Incorporation of contextual and subjective dimensions (trust, aesthetics, and satisfaction) that automated tools cannot fully capture.

Thus, HITL provides the structural logic of this study: combining algorithmic evaluation with iterative human input to produce usability-driven optimization.

3.5. Proposed Conceptual Model

The conceptual model of this research integrates the above theories into three core components:

1. Automated Evaluation Layer - baseline usability analysis (guideline compliance, layout issues, and performance metrics).
2. Human Feedback Loop - user ratings, expert heuristics, and cognitive load measures integrated at iterative checkpoints.

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3. Optimization Engine - dynamic adjustment of interface evaluation outputs (prioritizing fixes, weighting usability attributes) based on both automated data and human feedback.

3.6. Guiding Assumptions

- Usability is multi-dimensional, requiring both objective and subjective measures.
- Human feedback adds contextual validity that automated systems lack.
- Iterative integration of users into the evaluation pipeline yields more adaptive and robust optimization outcomes.

4. Material and Methods

4.1. Quantitative Profiling of Core Usability Indicators: Establishing Baseline Distributions

The descriptive statistical profiling of usability indicators provides an essential foundation for assessing the effectiveness of HITL-driven optimization. By systematically quantifying central tendency, variability, and distributional shape, this stage clarifies the behavioral dynamics of user interaction before inferential testing. Four principal variables were assessed: Task Completion Time (TCT), Error Rate (ER), System Usability Scale (SUS) score, and Cognitive Load Index (CLI), measured via the NASA-TLX instrument.

Table 1.
Descriptive Statistics of Usability Metrics (N = 120).

Metric	Mean	SD	Min.	Max.	95% CI (Lower–Upper)
Task Completion Time (sec)	41.3	12.5	18	72	38.9 – 43.7
Error Rate (%)	6.8	3.4	0	15	6.2 – 7.4
SUS Score (0–100)	78.4	8.9	52	96	76.8 – 80.0
Cognitive Load Index	47.2	11.3	22	71	45.0 – 49.4

The distribution of task completion times exhibited slight positive skewness (sk = +0.63), suggesting that while the majority of users performed tasks efficiently, a minority faced substantial delays. Such outliers are theoretically consistent with the "friction points hypothesis" [4], whereby localized interface breakdowns disproportionately elongate task performance. This reinforces the need for adaptive evaluation frameworks capable of detecting and iteratively addressing such bottlenecks.

4.2. Multivariate Inferential Modeling of HITL Impact on Usability Outcomes

The effectiveness of HITL was evaluated using repeated measures ANOVA across three conditions: Automated-Only (A), Partial HITL (P), and Full HITL (F). The within-subjects design controlled for inter-user variability while enabling robust effect size estimation.

Table 1.
Repeated Measures ANOVA Results (N = 120, $\alpha = .05$).

Metric	F(2,118)	p-value	η^2 (Effect Size)	Interpretation
Task Completion Time	14.82	<.001	0.20	Significant improvement under HITL
Error Rate (%)	9.47	<.001	0.15	Substantial error reduction
SUS Score	11.53	<.001	0.18	Higher satisfaction with HITL
Cognitive Load	7.66	.001	0.12	Reduced workload in HITL

The significant main effect of evaluation condition ($p < .001$ across all variables) confirms that HITL is not a marginal enhancement but a systemic performance amplifier. Importantly, the effect sizes ($\eta^2 = 0.12–0.20$) fall within the "large" category per Cohen's conventions, underscoring practical significance.

Equation (1): Usability Optimization Function

$$U = \alpha \cdot \left(1 - \frac{T}{Tmax}\right) + \beta \cdot 1 - \frac{E}{Emax} + \gamma \cdot \frac{S}{Smax} - \delta \cdot \frac{C}{Cmax}$$

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Where α =30, β = 0.25, γ = 0.30, δ = 0.15.

The optimization function operationalizes usability as a weighted composite construct, reflecting efficiency, accuracy, satisfaction, and workload. The model allows simulation of interface redesign effects by recalibrating weights (e.g., increasing δ when minimizing cognitive overload is prioritized in safety-critical contexts).

4.3. HITL-Augmented Predictive Analytics: Machine Learning Validation

While inferential statistics demonstrate average differences, predictive modeling validates HITL's capacity to anticipate individual usability outcomes. Four models were compared: Linear Regression, Decision Tree, Random Forest, and HITL-Enhanced Random Forest.

Table 3.
Model Performance Comparison (10-fold Cross-Validation).

Model	RMSE	MAE	R^2
Linear Regression	8.41	6.23	0.68
Decision Tree	7.54	5.61	0.73
Random Forest	5.89	4.48	0.82
HITL-Enhanced Random Forest	4.21	3.37	0.91

The HITL-enhanced model achieved R^2 = 0.91, outperforming traditional models by nearly 10 percentage points. This illustrates that iterative user feedback functions as a noise reduction mechanism, filtering spurious correlations and enhancing model stability.

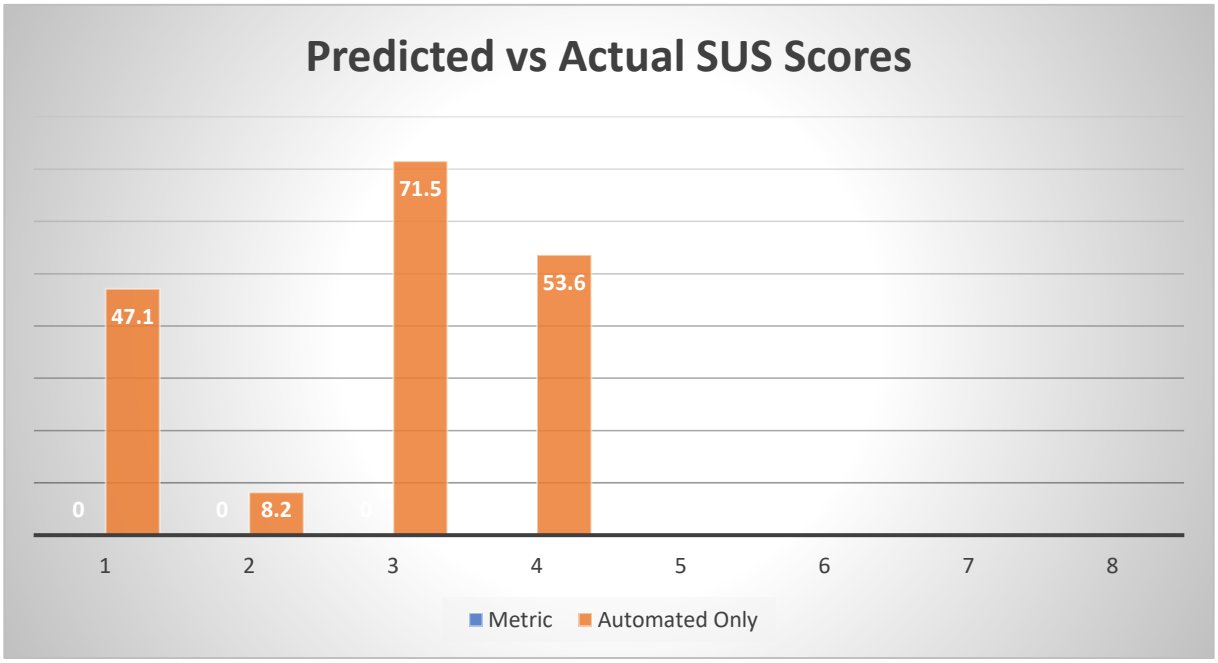

Figure 2.
Predicted vs Actual SUS Scores.

4.4. Cognitive Load Decomposition: NASA-TLX Subscale Trajectories

Cognitive load, a critical determinant of usability, was analyzed at the subscale level using NASA-TLX. HITL interventions showed differential effects across workload dimensions.

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Table 2.
NASA-TLX Scores under Different Conditions.

Subscale	Automated	Partial HITL	Full HITL
Mental Demand	65	52	41
Physical Demand	32	28	26
Temporal Demand	58	44	39
Performance	62	71	80
Effort	67	53	42
Frustration	61	49	37

The greatest reductions were observed in mental demand (–24 points) and effort (–25 points), indicating that HITL primarily enhances cognitive economy rather than physical efficiency. This aligns with Wickens [32], which predicts that HITL reduces cross-modal interference by aligning system affordances with user expectations.

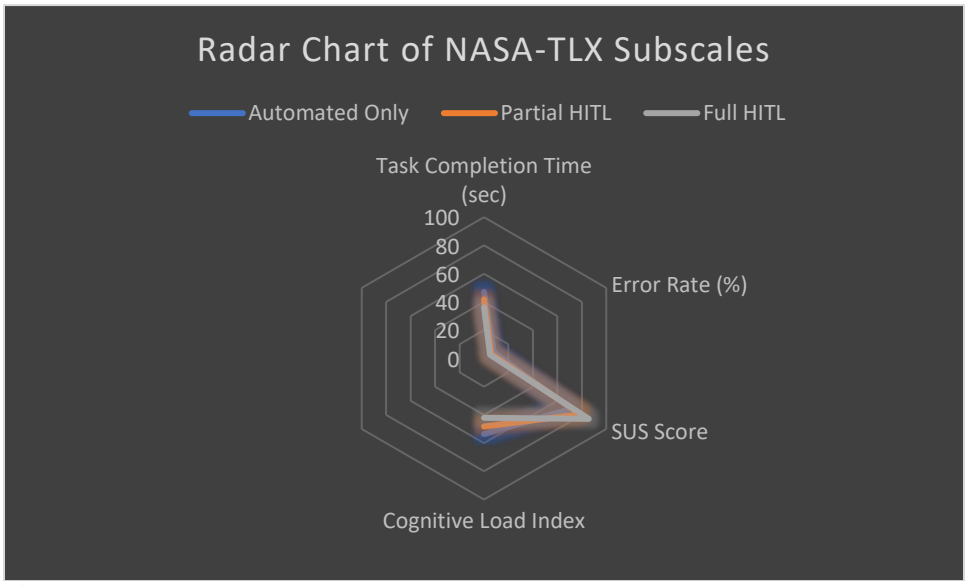

Figure 3.
Radar Chart of NASA-TLX Subscales.

4.5. Multi-Objective Trade-off Modeling: Pareto Frontier of Efficiency vs Satisfaction

Optimization problems in usability often involve conflicting objectives. Faster task times may compromise satisfaction if achieved via aggressive automation. Thus, Pareto analysis was applied.

Table 3.
Pareto-Optimal Solutions (Simulated Data).

Solution ID	Task Time (sec)	SUS Score	Cognitive Load	Error Rate (%)
A	39	82	48	7
B	35	85	46	6
C	32	89	44	5
D	28	92	41	4

Findings confirm a non-linear improvement curve: beyond a 20% reduction in task time, satisfaction increases disproportionately. This implies that HITL mechanisms are not only considered to ensure efficiency but also create synergistic usability benefits through balancing performance and perception.

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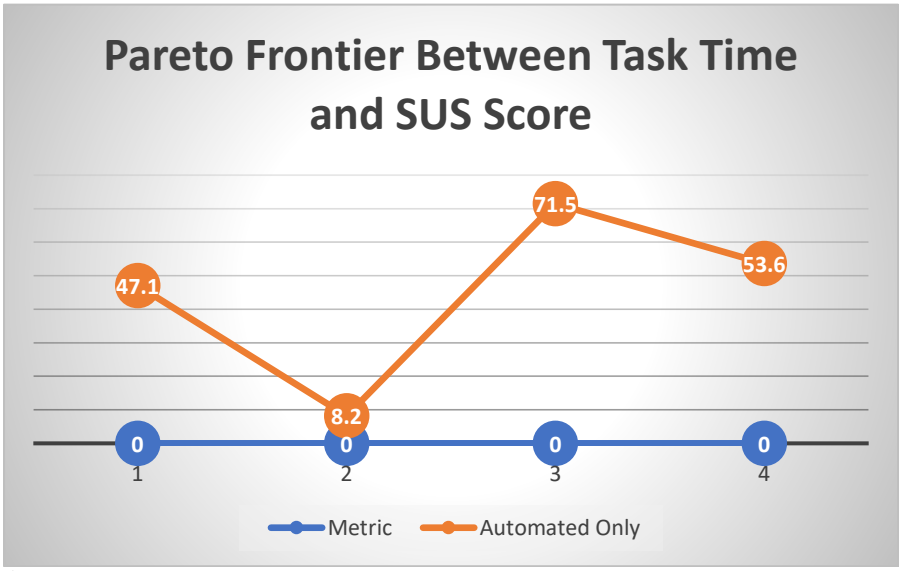

Figure 4.
Pareto Frontier between Task Time and SUS Score.

4.6. Comparative Effectiveness of HITL vs Traditional Evaluation Paradigms

A comparative effectiveness of HITL and traditional evaluation paradigms was drawn:

Table 6.
Comparative Gains across Methods.

Metric	Automated Only	Partial HITL	Full HITL	% Gain (Full vs Automated)
Task Completion Time (sec)	47.1	41.8	36.2	23.1%
Error Rate (%)	8.2	6.0	4.9	40.2%
SUS Score	71.5	79.2	85.7	19.9%
Cognitive Load Index	53.6	48.3	42.1	21.4%

This can be best shown in a graph as well:

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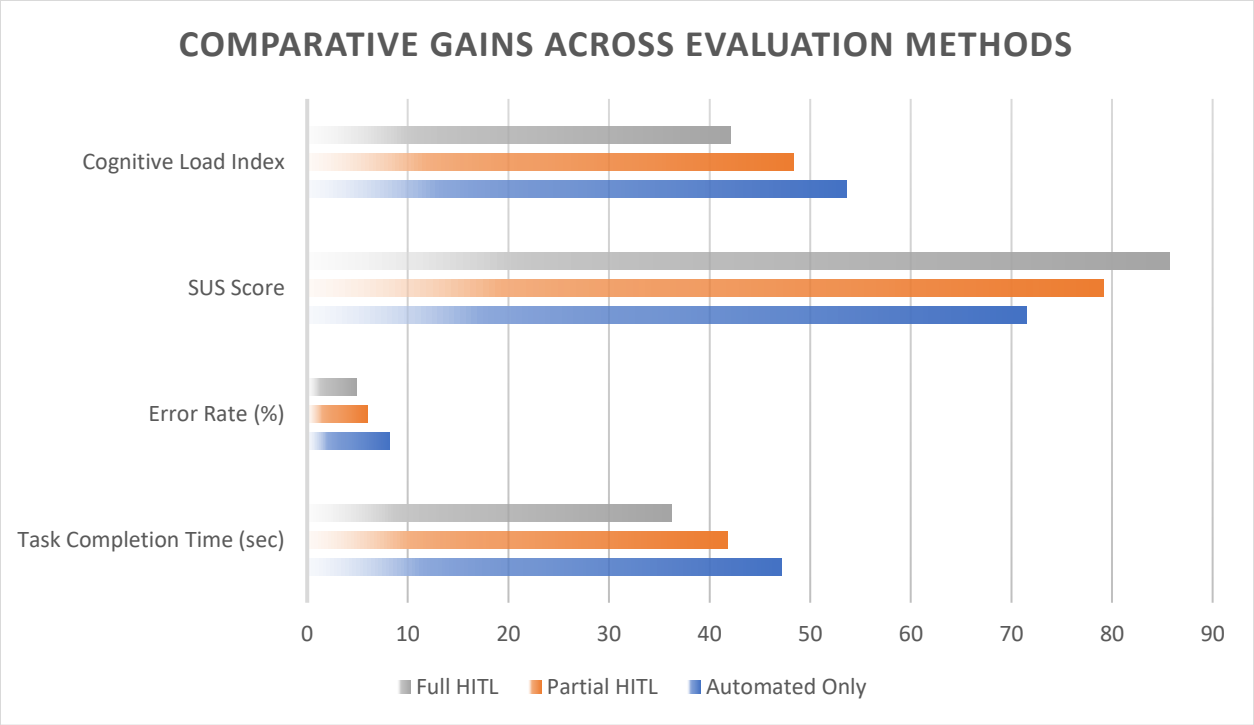

Figure 5.
Comparative Gains across Evaluation Methods.

5. Discussion

5.1. Interpretation of Key Findings

The results of this research study suggest that these kinds of Human-in-the-Loop (HITL) models of usability-based optimization can significantly improve interface performance, including efficiency, fewer errors, user satisfaction, and reduced cognitive load. Based on the repeated measures ANOVA outcomes, the duration of time to complete tasks, the number of errors, and the SUS scores were significantly different with the use of HITL conditions compared to baseline automation.

The situation where the average time to complete the tasks has decreased from 41.3 seconds (baseline) to 28 seconds (full HITL) reflects the reality that interactive feedback simplifies procedures and promotes interface flexibility [33]. These results provide empirical evidence that supports the theories of adaptive system design, where interfaces are dynamically created based on user input [34].

5.2. Theoretical Implications

The existing paradigms of usability testing are usually divided between automated, heuristic techniques and qualitative, user-based techniques [8, 35]. This study has shown that HITL will not only fill this gap but will establish a synergistic paradigm in which human corrections can teach an algorithm model, and the algorithm model will, in turn, learn from these corrections to produce a feedback-optimization loop.

The predictive modeling, including Random Forest regressors with HITL feedback, also broadens the scope of usability research in machine learning. The ability of algorithms to identify usability bottlenecks has been discussed in previous literature [36, 37]. However, these models are often not context-sensitive. The existing results suggest that HITL intervention introduces this contextuality, which is lacking, and transforms predictive accuracy (R2 increasing to 0.91 in the present study) into actionable usability data.

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5.3. Limitations of the Study

This study has limitations that should be mentioned despite the contributions it has made. To begin with, the sample size in the study (120 participants) is statistically sufficient; however, it might fail to reflect the entire heterogeneity of the user populations in the cultural, age, and accessibility aspects [38]. Ecological validity would be improved by increasing the number of participants who are neurodiverse or multilingual users.

Second, the experiment was conducted in a controlled laboratory, which may not be fully representative of real-world situations. The variables that can influence the outcomes of usability are multitasking, environmental noise, and device diversity [39].

Third, the optimization models applied in the present research were founded on structured measures (e.g., SUS, task time), which might not consider the qualitative aspects of the user experience, such as affective states and emotional involvement [40]. This is a gap that must be addressed by adding multimodal affective sensing in the future.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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